ESSAYS ON ASSET PRICING: PREDICTABILITY, INFORMATION, AND LIQUIDITY

A Dissertation

Presented to the Faculty of the Graduate School

of Cornell University

in Partial Fulfillment of the Requirements for the Degree of

Doctor of Philosophy

by

Qingqing Chen

May 2009

ESSAYS ON ASSET PRICING: PREDICTABILITY, INFORMATION, AND LIQUIDITY

Qingqing Chen, Ph.D.

Cornell University 2009

This dissertation is a collection of essays on Asset Pricing: Predictability, Information, and Liquidity.

The first chapter, "Predictability of Equity Returns over Different Time Horizons: A Nonparametric Approach", aims to test an important hypothesis in financial economics: whether equity returns are predictable over various horizons? We first propose a nonparametric test to examine the predictability of equity returns, which can be interpreted as a signal-to-noise ratio test. Our empirical results show that the short rate, dividend yields and earnings yields have good predictability power for both short and long horizons, which is different from both the conventional wisdom and Ang and Bekaert (2007). Also, using our nonparametric test, a comprehensive in-sample and out-of-sample analysis documents that the predictor variables (dividend yields, earnings yields, dividend payout ratio, short rate, inflation, book-to-market ratio, investment to capital ratio, corporate issuing activity, and consumption, wealth, and income ratio) have predictability power on equity returns but this cannot be well captured by linear prediction models. In addition, we use the nonparametric test to compare the conventional long-horizon prediction regression models on predictor variables with the historical mean model, where there has exists a debate about which model has better forecasting power for equity returns (Campbell and Thompson (2007) and Goyal and Welch (2007)). We find that the prevailing prediction model has a better forecasting power than the historical mean model because the former has a lower neglected signal-to-noise

ratio. Finally, we find that our nonparametric predictive models have lower RMSE than the historical mean model at both short-horizon and long-horizon. Using our nonparametric methods, both combined and individual forecast outperform the historical average.

The second chapter, "An Intraday Analysis of Related Investment Vehicles Traded in the NYSE and AMEX", undertakes an intraday analysis of related investment vehicles traded in the NYSE and AMEX. I investigate how the trading behaviors of three related investment vehicles (American Depository Receipt, Exchange-traded Fund, and Closed-end Fund) differ across countries using high-frequency intraday data. I find that ADRs trade at transaction prices that are on average worse than ETFs and CEFs. The trading of ADRs, ETFs, and CEFs follows positive feedback strategies. The buy and sell trades of the three securities are driven by the net order imbalances and past returns of three securities themselves. The correlated trading behaviors of the three securities can be explained by momentum traders with a common information set.

The third chapter, "Endogenous Information Acquisition, Cost of Capital, and Comovement of Equity Returns", investigates endogenous information acquisition, cost of capital, and comovement of equity returns. The traditional asset pricing model cannot provide a good explanation for the comovement of asset returns. This chapter introduces endogenous costly information acquisition that generates comovement of asset returns in a rational expectations framework. The private information signals observed by many investors contain information not only about the value of the asset itself, but also the value of many other assets. This common source of information causes excessive covariance in their returns. If informed investors acquire more private information, or more investors are informed, the comovement of asset returns will increase. On the other hand, if informed investors aggressively obtain abundant private information, the comovement will decrease. We also find that both greater precision in private information and higher cost of information will increase a company's cost of capital.

BIOGRAPHICAL SKETCH

Qingqing Chen was born in Wuhan, China. She graduated from Peking University in 2002, where she received her B.A. and M.A. in economics. Upon graduation, she joined the doctoral program of economics at Cornell University. In April 2009, she defended her doctoral dissertation. Her first position will be as a financial economist at the Office of the Comptroller of the Currency in Washington D.C.

To my family.

ACKNOWLEDGEMENTS

I am deeply indebted to my advisor, Professor Yongmiao Hong. He generously offered his time to discuss every idea I had and patiently guided me through all aspects of academic life. This thesis benefited tremendously from numerous discussions with him. I also thank him for his strong support and help during my PhD study. To me, Yongmiao is a leading example of academic integrity and scholarship, as well as a role model as an exceptionally generous person.

I am grateful to Robert Masson and Hazem Daouk for serving on my dissertation committee. They provided invaluable advice and insightful comments which led to significant improvements of this thesis.

I gratefully acknowledge the financial support I received from the Sage Fellowship and the Department of Economics.

The greatest thanks go to my family for their unconditional and infinite love, support, and encouragement. They always have faith in me and never asked for a reason why I spent so many years in school. Without them, it would have been impossible for me to come this far.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

Chapter 1
Introduction

Asset pricing is a traditional research area in financial economics. This is an important topic for academics, investment professionals, and policy makers. The asset pricing theory tries to understand why prices or returns are what they are. How financial economists understand the investment world has been changed over the decades. In the early 80's, researchers believe that stock and bond returns were essentially unpredictable. Towards the end of the last century, academic researchers came to take seriously the view that aggregate stock returns are predictable. A new generation of empirical research in the late twenty century does substantially enlarge our view of "what activities provide rewards for holding risks, and they challenge our understanding of those risk premiums".

The predictability of long-horizon returns has drawn great interests from researchers. Different economic predictors, predictive regression models, and sample periods and frequencies are used in numerous research papers. However, there is not much consensus on what drives this predictability and predictability power over different time horizons (specifically at long horizons). The first essay of my dissertation provides some useful evidence for the recent debates on return predictability in the finance literature. Long-horizon asset returns are more informative than their shorter-horizon counterparts, so random walk models, and martingale models based on past asset returns are statistically weak to explain real data. It is more reasonable to study the price behavior using the models of asset returns in economics or finance. The most popular model which is used to predict asset returns is the discounted-cash-flow or present-value model explored by Rozeff (1984), Campbell and Shiller (1987), Campbell and Shiller (1988a, 1988b), and West (1988). This model relates the price of a stock to its expected future cash flows (i.e., its dividends) discounted to the present value using a constant or time-varying discount rate. Existing studies suggest that there exists strong non-linearity in the models of predicting asset returns, and that expected asset returns and dividend ratios are highly persistent and time-varying.

The current research point out several problems and propose new methods or approaches to evaluate or improve the predictability power of equity returns. First, the apparent predictability of stock returns might be spurious given the fact that many predictor variables, such as valuation ratios, are highly persistent (Nelson and Kim (1993); Stambaugh (1999); Cavanagh et al. (1995); Foster et al., 1997; Ferson, Sarkissian, and Simin (2003); Sarkissian, and Simin (2003)). Second, there exists serial correlation in the forecast error particularly when the time horizon h is large relative to the sample size. As a result, there exist some finite sample problems for reliable statistical inference (Hodrick (1992), Nelson and Kim (1993)). An active recent literature discusses alternative econometric methods or proposes new statistical tests for correcting the bias and conducting valid inference on estimation of long-horizon predictive regression models with persistent variables and errors. Third, the VAR model cannot fully capture the nonlinear dynamics of dividend yields implied by the present value model (Hodrick (1992), Campbell and Shiller (1988a, b), Stambaugh (1999)). A linear predictive regression model sometimes neglects nonlinear predictability. Fourth, a different critique emphasizes that the most linear predictive regressions have often performed poorly out-of-sample (Goyal and Welch (2003, 2007); Campbell and Thompson (2007)).

Moreover, there are two recent debates on the predictability of equity premiums in the literature. First, most of the theoretical and empirical work focuses on the predictive prowess of the dividend yield, especially at long horizons. The conventional wisdom in the literature is that aggregate dividend yields strongly predict excess returns, and the predictability is stronger at longer horizons (Fama and French (1988), Campbell (1991), and Cochrane (1992)). The results at different horizons are reflections of a single underlying phenomenon. If daily returns are very slightly predictable by a slow-moving or persistent variable, then predictability adds up over long horizons. In contrast, Ang and Bekaert (2007) find that dividend yields, together with the short rate, predict excess returns only at short horizons and do not have any long-horizon predictive power. On the other hand, Goyal and Welch (2007) argue that the historical average excess stock return forecasts future excess stock returns better than regressions of excess returns on predictor variables. In response to their arguments, Campbell and Thompson (2007) show that many predictive regressions beat the historical average return by imposing restrictions on the signs of coefficients and return forecasts, or the coefficients relating valuation ratios to future returns based on steady-state models. The conclusions of the two debates are controversial.

In this essay, we undertake an analysis of both in-sample and out-of-sample tests of stock return predictability in an effort to better understand the empirical evidence on return predictability. We are particularly interested in investigating the following problems: (1) Does the predictability of valuation ratios such as dividend yields exist at various horizons? (2) Do linear predictor variables-based regression models suffer from neglected nonlinear predictability? In particular, is the poor out-of-sample performance of most linear prediction models due to the limitation of linear models or due to the nonexistence of predictability of equaity returns? (3) Does the predictor-based regression model beat the historical average excess stock return (historical mean model)?

We propose a reliable out-of-sample nonparametric model-free predictability test to examine whether there exists the predictability of equity returns at short or long horizons. Ang and Bekaert (2007) find that dividend yields, together with the short rate, predict excess returns only at short horizons. In contrast, we find that the short rate, dividend yields, and earnings yields have good predictability power at both short and long horizons. Second, the comprehensive in-sample and out-of-sample analysis suggests that such variables as dividend yields, earnings yields, dividend payout ratio, short rate, inflation, book-to-market ratio, investment to capital ratio, corporate issuing activity, and consumption, wealth, and income ratio have predictability power for equity returns, but this often cannot be captured by popular linear regression models. Third, we find that the prevailing prediction model beats the historical mean model because there is more neglected signal-to-noise ratio for the latter. Our conclusion is in contrast to Goyal and Welch (2007), and is consistent with Campbell and Thompson (2007), who find that predictor variables perform better out-of-sample than the historical average return forecasts, once weak restrictions are imposed on the signs of coefficients and return forecasts, or the coefficients relating valuation ratios to future returns based on steady-state models.

We use a nonparametric estimator to predict the equity returns following the same logic of our nonparametric test. Our nonparametric predictive models have lower RMSE than the historical mean model at both short-horizon and long-horizon. Our nonparametric prediction can improve the out-of-sample performance without restrictions. Using our nonparametric methods, both combined and individual forecast outperform the historical average. One reasonable explanation is that the nonparametric predictive model can fit the equity return better based on the predictors. It is not restricted to the parametric forms. It can fit the data better than the linear or nonlinear parametric model.

If the investment world does not obey a model's predictions, we can decide that the model needs improvement. However, we can also decide that the investment world is wrong, that some assets are "mispriced" and present trading opportunities for the shrewd investor. This latter use of asset pricing theory accounts for much of its popularity and practical application. One possible application is to investigate the trading behaviors of the different securities. The questions money managers are interested in are (1) what are the trading pattern of different securities? (2) what are the best trading strategies to manage a portfolio or basket in order to maximize profits and minimize risks? Investigating those questions is important not only for us to understand the determinants of trading volume, liquidity, and stock returns but also for money managers and policymakers to devise efficient trading strategies and improve the liquidity and efficiency of financial markets.

There is a vast amount of literature on how investors trade. DeLong, Shleifer, Summers, and Waldmann (1990) show that passive traders and rational speculators trade on firm fundamentals and/or superior information, while positive-feedback traders simply buy when prices rise and sell when prices fall. Hong and Stein (1999) show that momentum traders can make profit by implementing simple strategies such as trendchasing. A number of large and presumably sophisticated money managers use momentum approaches. Diversification into global equity markets is one of the approaches for money managers to improve the risk/return trade-off of a stock portfolio.

The second essay of my dissertation is to investigate the trading behaviors of three similar trading vehicles: American depositary receipts (ADR), exchange-traded funds (ETF), and closed-end funds (CEF), which specialize in holding a portfolio of foreign equities of one country or a group of countries in a region on US stock exchanges. I focus on how the trading activities differ, in real time, among ADR, ETF, and CEF. First, this essay examines whether ADR, ETF, and CEF trade at different transaction prices across countries. It helps me to understand whether one type of security have an advantage of trading over the other. Second, I use the VAR model to estimate the correlations of return, volume, liquidity, and volatility among the three securities. It shows the relative relation of trading among the three securities. Third, I examine the short-horizon dynamic relation between the order imbalance and both past and subsequent returns by type of securities using high-frequency intraday data. I find that ADRs trade at transaction prices that are on average worse than ETFs and CEFs. The trading of ADRs, ETFs, and CEFs follows positive feedback strategies. The buy and sell trades of the three securities are driven by the net order imbalances and past returns of three securities themselves. The correlated trading behaviors of the three securities can be explained by momentum traders with a common information set.

Another application is to investigate how the endogenous information acquisition and cost of capital affect the comovement of equity returns. The study of the comovement of asset returns has recently received great interests in finance literature. The cause of stock market covariation remains a puzzling issue. There are different theories that explain the comovement of the asset returns. Researchers have uncovered numerous patterns of comovement in asset returns. There are strong common factors in the returns of small-cap stocks, value stocks, closed-end funds, stocks in the same industry, and bonds of the same rating and maturity.

There is common movement of individual stocks within national markets and also among international markets.

The traditional asset pricing theory shows that comovement in returns must be due to correlation in fundamental value. We call it fundamentals-based comovement. In behaviour literature, there exists an alternative theory which argues that return comovement is delinked from fundamentals due to market frictions or noise-trader sentiment. "Friction-based" and "sentiment-based" comovement come from three specific variables: the category, habitat, and information diffusion views (Barberis, Shleifer, and Wurgler (2005)). Empirical evidence cannot easily be explained by the fundamentals-based view of comovement so many scholars think it might be evidence of investor irrationality and fit with the friction-based or sentiment-based views. We want to revisit traditional asset pricing theory by introducing information market and try to give a good explanation for comovement of asset returns. We call it information-based comovement.

Trading based on private information and cost of information acquisitions could be potential causes of the comovement in stock returns if agents have superior knowledge about the common factors of the stock returns. On the other side, it is very common to explain why individuals trade assets in stock markets because of their access to different information. To motivate differences in information, it is typically assumed that information is costly to acquire, so that some agents will buy information and some will not. But this explanation raises a lot of interesting questions: How much information will be acquired about stocks? How will this information be reflected in prices? How do informed and uninformed traders interact with one another? Does cost of the information acquisition affect the returns? Yet it is challenging to answer these questions. The reason is that in an equilibrium where information is costly to acquire, agents who choose not to purchase information nevertheless extract some information from the prices they observe, and so their demand will depend on the distribution of equlibrium prices. Information-based comovement has not been widely accepted because it is difficult to model information acquisitions and test the comovement based on data of investors' information.

The third essay of my dissertation introduces endogenous costly information acquisition that generates comovement of asset returns in a rational expectations framework. The private information signals observed by many investors contain information not only about the value of the asset itself, but also the value of many other assets. This common source of information causes excessive covariance in their returns. If informed investors acquire more private information, or more investors are informed, the comovement of asset returns will increase. On the other hand, if informed investors aggressively obtain abundant private information, the comovement will decrease. We also find that both greater precision in private information and higher cost of information will increase a company's cost of capital.

This dissertation is organized as follows. Chapter 2 is "Predictability of Equity Returns over Different Time Horizons: A Nonparametric Approach". Chapter 3 is "An Intraday Analysis of Related Investment Vehicles Traded in the NYSE and AMEX". Chapter 4 is "Endogenous Information Acquisition, Cost of Capital, and Comovement of Equity Returns". Chapter 5 concludes.

Chapter 2
Predictability of Equity Returns over Different Time Horizons: A Nonparametric Approach

2.1 INTRODUCTION

There is a long tradition in finance and economics to study the predictability of equity returns or equity premiums. Cochrane (1999) points out that one of financial economist's views about the investment world was that returns are unpredictable until the mid-1980. Towards the end of the last century, academic researchers came to take seriously the view that aggregate stock returns are predictable[1]. Fundamental economic forces are crucial determinants of equity premia in financial markets.[2] The vast literature has suggested that excess returns are predictable by such variables as dividend-price ratios, earnings-price ratios, dividend-earnings ratios, short rates, book-to-market ratio, and an assortment of other financial indicators.

The predictability of long-horizon returns has drawn great interests from researchers. Long-horizon asset returns are more informative than their shorter-horizon counterparts, so random walk models, and martingale models based on past asset returns are statistically weak to explain real data. It is more reasonable to study the price behavior using the models of asset returns in economics

[1] A new generation of empirical research in the late twenty century does substantially enlarge our view of "what activities provide rewards for holding risks, and they challenge our understanding of those risk premiums".

[2] Equity risk premia are closely related to economic conditions. Equity returns seem to be high at business cycle troughs and low at peaks. In line with the pioneering work by Ferson and Merrick (1987), Fama and French (1989), researchers suggest that predictors of excess returns should be correlated with economic conditions. Lettau and Ludvigson (2005) summarize the literature and point out that we should expect to find evidence from predictive regressions of excess returns on macroeconomic variables over business cycle horizons."

or finance. The most popular model which is used to predict asset returns is the discounted-cash-flow or present-value model explored by Rozeff (1984)[3], Campbell and Shiller (1987), Campbell and Shiller (1988a, 1988b)[4], and West (1988). This model relates the price of a stock to its expected future cash flows (i.e., its dividends) discounted to the present value using a constant or time-varying discount rate. The present value model assumes that the expected stock return is constant through time and makes no assumption about equity repurchases by firms which affect the time pattern of expected future dividends. While stock prices and dividends appear to grow exponentially over time rather than linearly, the linear model (even allowing for a unit root) is less appropriate than a nonlinear model which can better capture the properties of asset returns across time. Thereafter, researchers have proposed several nonlinear models to explain or predict asset returns. One is the dividend models with rational bubbles in which the bubble is a nonlinear function of the stock's dividends (Froot and Obstfeld (1991)). This nonlinear model with stochastic rational bubbles has its limitation in explaining the observed predictability of stock returns. Another nonlinear model is a loglinear present-value model (Campbell (1991), Ang and Bekaert (2007)), which suggests a nonlinear relation between equity returns and dividend ratio, interest rates, excess returns, or cash flows. The loglinear model can capture the asset price behavior without imposing restrictions on the expected returns. These studies suggest that there exists

[3]Rozeff (1984) showed that dividend yields can forecast equity risk premia by a deterministic dividend discount model. For example, Under the Gordon growth model, $P_t = \sum_{i=1}^{\infty} \frac{D_t(1+g)^i}{(1+r)^i} = \frac{D_{t+1}}{r-g}$, where P is the stock price, D is the dividend, r is the discount rate, and g is the constant growth rate of dividend. In the certainty model, the discount rate is the expected return on the stock. If the stock price represents a claim to the future stream of dividends, the price can be exactly determined assuming constantly growing dividends and a known discount rate and the model suggests that dividend yields should capture variations in expected stock returns.

[4]Campbell and Shiller (1988a, 1988b) develop a stochastic approximation to the dividend discount model and estimate the model in a VAR framework.

strong nonlinearity in the models of predicting asset returns, and that expected asset returns and dividend ratios are highly persistent and time-varying. Thus, it is important to investigate the predictive relationship between asset returns and time horizons.

There are quite a few works which examine the predictive power of the dividend yield on excess stock returns over various time horizons. Fama and French (1988), Campbell and Shiller (1988a,b), and Nelson and Kim (1993) document evidence of predictability. However, empirical studies increasingly cast doubt on the forecasting power of price-based predictors of equity returns. There are two recent debates on the predictability of equity premiums in the literature. First, most of the theoretical and empirical work focus on the predictive prowess of the dividend yield,[5] especially at long horizons. The conventional wisdom in the literature is that aggregate dividend yields strongly predict excess returns, and the predictability is stronger at longer horizons (Fama and French (1988)[6], Campbell (1991), and Cochrane (1992)). The results at different horizons are reflections of a single underlying phenomenon. If daily returns are very slightly predictable by a slow-moving or persistent variable, then predictability adds up over long horizons. In contrast, Ang and Bekaert (2007) find that dividend yields, together with the short rate, predict excess returns only at short horizons and do not have any long-horizon predictive power. On the other hand, Goyal and Welch (2007) argue that the historical average excess stock return forecasts future excess stock returns

[5] Fama and French (1988), Campbell and Shiller (1988a,b), Goetzmann and Jorion (1993, 1995), Hodrick (1992), Stambaugh (1999), Wolf (2000), Goyal and Welch (2003, 2007), Valkanov (2003), Lewellen (2004), Campbell and Yogo (2006), Campbell and Thompson(2007), and Ang and Bekaert (2007)

[6] Fama and French (1988) provide the strongest evidence in support of the dividend yield effect by using overlapping multiple-year horizon returns. They observe that the explanatory power of the dividend yield increases with the time horizon of the returns; over 4-year horizons, the R^2's reach an astonishing high value of 64%.

better than regressions of excess returns on predictor variables. In response to their arguments, Campbell and Thompson (2007) show that many predictive regressions beat the historical average return by imposing restrictions on the signs of coefficients and return forecasts, or the coefficients relating valuation ratios to future returns based on steady-state models. The conclusions of the two debates are controversial.

Most of the existing empirical studies use linear regressions to forecast asset returns. There are a number of pitfalls applying those models to predict asset returns or evaluate the predictability power. First, several authors expressed concern that the apparent predictability of stock returns might be spurious given the fact that many predictor variables, such as valuation ratios, used are highly persistent. Nelson and Kim (1993) and Stambaugh (1999) pointed out that persistence leads to biased coefficients in predictive regressions if innovations in the predictor variable are correlated with returns (as is strongly the case for valuation ratios, although not for interest rates). Under the same conditions, the standard t-test for predictability has incorrect sizes in finite samples (Cavanagh et al., 1995). These problems become more serious if applied econometricians are data mining, considering large numbers of variables, and reporting only those results that are apparently statistically significant (Foster et al., 1997; Ferson, Sarkissian, and Simin, 2003). Sarkissian, and Simin (2003) explore spurious regressions and data mining in the presence of serially correlated explanatory variables and they conclude that many regressions based on individual predictor variables may result in spurious conclusions. Second, another problem is that the explanatory variable, the dividend yield, is not properly exogenous, but rather contains a price level that also appears in the regression (Stambaugh (1986)). Moreover, Fama and French

(1988) point out an "errors-in-variables" problem due to the fact that yields contain forecasts of future returns and dividend growth. This may bias downward the regression coefficient in the dividend yield regression. Fama (1990) and Kothari and Shanken (1992) suggest that the errors-in-variables problem is a potentially major one, since a significant percentage of return variance may be explained by changes in the growth rate of future dividends.

Third, there exists serial correlation in the forecast error particularly when the time horizon h is large relative to the sample size. As a result, there exist some finite sample problems for reliable statistical inference (Hodrick (1992), Nelson and Kim (1993)). An active recent literature discusses alternative econometric methods or proposes new statistical tests for correcting the bias and conducting valid inference on estimation of long-horizon predictive regression models with persistent variables and errors.[7] These studies have emphasized the bias toward rejection of the null hypothesis of no predictability. In particular, the usual corrections to the standard errors are only valid asymptotically, and there is some question as to whether "asymptotic" should be measured in terms of years, decades, or even centuries, especially for long-horizon forecasts. Hodrick (1992) examines the implications for hypothesis testing of using different specifications of the forecasting equation. Nelson and Kim (1993) analyze small-sample biases in simulations of a VAR system for returns and yields, under the null hypothesis of no predictability of returns. Using U.S. returns sampled annually, they report that the simulated distributions of t-statistics are displaced upward, and still find some spurious evidence of predictability at conventional significance levels. In the case of the dividend yield regression, however, price levels appear in both the regressor and the regressand.

[7] See Cavanagh et al., 1995; Mark, 1995; Kilian, 1999; Lewellen, 2004; Campbell and Yogo, 2006; Polk et al., 2006; Ang and Bekaert, 2007; Valkanov, 2003

From the work of Dickey and Fuller (1976) and Stambaugh (1986), it is well-known that regressions on lagged dependent variables lead to biased coefficient estimates. Goetzmann and Jorion (1993) use the bootstrap methodology, as well as simulations, to examine the finite sample distribution of test statistics under the null hypothesis of no forecasting ability. These experiments are constructed so as to maintain the dynamics of regressions with lagged dependent variables over long horizons (up to four years). They find that the empirically observed statistics are well within the 95% bounds of their simulated distributions and overall there is no strong statistical evidence indicating that dividend yields can forecast excess equity returns. Wolf (2000) uses a new statistical method for finding reliable confidence intervals for regression parameters in the context of dependent and possibly heteroscedastic data, called subsampling and does not find convincing evidence for the predictability of stock returns. Ang and Bekaert (2007) find that excess return predictability by the dividend yield is not statistically significant at longer horizons or across countries and also uses the nonlinear present value model to examine the fit of regression-based expected returns with true expected returns. Consistent with the data, they find that a univariate dividend yield regression provides a rather poor proxy for the true expected return. However, using both the short rate and dividend yield considerably improves the fit, especially at short horizons.

Fourth, while previous studies model returns and dividend yields using a finite-order VAR system (Hodrick (1992), Campbell and Shiller (1988a,b), Stambaugh (1999)), the VAR model cannot fully capture the nonlinear dynamics of dividend yields implied by the present value model. Indeed, for a linear predictive regression model, when a price-based estimator or regressor appeals to be statistically insignificant, one cannot conclude that the null hypothesis of no predictability holds, because there may exist neglected nonlinear predictability. Fifth, a different critique[8] emphasizes that the most linear predictive regressions have often performed poorly out-of-sample (Goyal and Welch (2003, 2007); Campbell and Thompson (2007)). It is well-known that while in-sample diagnostic analysis is important and can reveal useful information on possible sources of model misspecification, it may cause overfitting and capture spurious predictability. Out-of-sample evaluation can capture the true predictability of a model or the data generating process.[9] The disparities between in-sample and out-of-sample test results of return predictability documented in the literature make an overall assessment of return predictability difficult. In particular, it is unclear whether the poor out-of-sample performance of linear prediction models is due to the limitation of linear models or due to the nonexistence of predictability of equity returns. Many of the earlier out-of-sample tests have focused on the dividend ratios. Fama and French (1988) interpret the out-of-sample performance of dividend ratios to have been a success. Bossaerts and Hillion (1999) interpret the out-of-sample performance of the dividend yield (not dividend price ratio) to be a failure. Torous and Valkanov (2000) find that a low signal-noise ratio of many predictive variables makes a spurious relation between returns and persistent predictive variables unlikely and would lead to no out-of-sample forecasting power. Rapach and Wohar (2006) explore out-of-sample

[8]This critique had a particular force during the bull market of the late 1990s, when low valuation ratios predicted extraordinarily low stock returns that did not materialize until the early 2000s (Campbell and Shiller, 1998).

[9]Here are several important reasons why out-of-sample predictability check is important. First, the usual practice of extensive search for more complicated models using the same or similar data set may suffer from the so-called data snooping bias, as pointed out by Lo and MacKinlay (1989) and White (2000). A more complicated model may overfit idiosyncratic features of the data without capturing the true data generating process. Out-of-sample prediction evaluation will alleviate, if not eliminate completely, such data snooping bias. Second, a model that fits in-sample data well may not predict the future well because of unforeseen structural changes or regime shifts in the data generating process.

performance for a number of variables and find that certain financial variables display significant in-sample and out-of-sample predictive ability with respect to stock returns. Goyal and Welch (2007) argue that the poor out-of-sample performance of predictive regressions is a systemic problem. They compare predictive regressions with historical average returns and find that historical average returns almost always generate superior return forecasts. They conclude that "the profession has yet to find some variable that has meaningful and robust empirical equity premium forecasting power." Campbell and Thompson (2007) find that most of these predictor variables perform better out-of-sample than the historical average return forecast, once weak restrictions are imposed on the signs of coefficients and return forecasts. The out-of-sample explanatory power is small, but nonetheless is economically meaningful for investors. They also impose theoretical restrictions on the coefficients relating valuation ratios to future returns and theoretically restricted valuation models often outperform return forecasts based on the long-run historical mean of stock returns.

In this paper, we undertake an analysis of both in-sample and out-of-sample tests of stock return predictability in an effort to better understand the empirical evidence on return predictability. We are particularly interested in investigating the following problems:

- Does the predictability of valuation ratios such as dividend yields exist at various horizons?

- Do linear predictor variables-based regression models suffer from neglected nonlinear predictability? In particular, is the poor out-of-sample performance of most linear prediction models due to the limitation of linear models or due to the nonexistence of predictability of equaity returns?

- Does the predictor-based regression model beat the historical average excess stock return (historical mean model)?

For these purposes, we first develop a reliable out-of-sample nonparametric model-free predictability test, which has several appealing features. First, as is well-known, the nonparametric method can capture a wide variety of linearities and nonlinearities without assuming any parametric model. Thus, it can assess directly the predictability of equity return data itself rather than the predictability of a specific model for equity return. Second, the nonparametric predictability test can be interpreted as a signal-to-noise ratio, because it is based on the average of the squared predictable components over the sample variance of pricing errors. Third, we propose to use a conditional bootstrap procedure which maintain the original dynamics of predictor variables and serial dependence structure of the multi-step-ahead forecast errors. Such a bootstrap procedure provides reliable statistical inference for sample sizes typically encountered in the literature. Simulation studies show that it has reasonable size and power in finite samples even when the regressors are highly persistent and the forecast horizon is relatively long.

We apply the proposed nonparametric test to examine whether there exists the predictability of equity returns at short or long horizons. Ang and Bekaert (2007) find that dividend yields, together with the short rate, predict excess returns only at short horizons. In contrast, we find that the short rate, dividend yields, and earnings yields have good predictability power at both short and long horizons. Second, the comprehensive in-sample and out-of-sample analysis suggests that such variables as dividend yields, earnings yields, dividend payout ratio, short rate, inflation, book-to-market ratio, investment to capital ratio, corporate issuing activity, and consumption, wealth, and income ratio have predictability power for equity returns, but this often cannot be captured by popular linear regression models. Third, we find that the prevailing prediction model beats the historical mean model because there is more neglected signal-to-noise ratio for the latter. Our conclusion is in contrast to Goyal and Welch (2007), and is consistent with Campbell and Thompson (2007), who find that predictor variables perform better out-of-sample than the historical average return forecasts, once weak restrictions are imposed on the signs of coefficients and return forecasts, or the coefficients relating valuation ratios to future returns based on steady-state models. In fact, the restriction on coefficients is a form of nonlinearity.

In the literature, most papers focus on a set of predictors based on theoretical models. From an academic viewpoint, the use of model-based predictors facilitates an understanding of specific aspects of the economic mechanism. From an investor's viewpoint, however, these predetermined variables may not be enough to capture all information required in decision making. Forecast combination has recently received renewed attention in the forecasting literature; Stock and Watson (1999, 2003, 2004) with respect to forecasting inflation and real output growth. Rapach, Strauss, and Zhou (2009) propose a combination approach to improve the out-of-sample equity premium forecasting problem. In addition to the individual forecast, we also consider the combined forecast to improve equity premium forecasts, and examine the out-of-sample performance. On the other hand, previous studies suggest that there exists strong nonlinearity in the models of predicting asset returns, and that expected asset returns and dividend ratios are highly persistent and time-varying. The poor out-of-sample performance of most linear prediction models is due to the limitation of linear models. The lack of consistent out-of-sample evidence in Goyal and Welch (2008) indicates the need for improved forecasting methods to better establish the empirical reliability of equity premium predictability. In this paper, we propose nonparametric estimators to forecast the equity returns using both individual forecast and combined forecast.

Goyal and Welch (2007) argue that the historical average excess stock return forecasts future excess stock returns better than regressions of excess returns on predictor variables. With respect to the economic variables used to predict the equity premium, we use the 15 economic variables from Goyal and Welch (2008) to predict the individual predictive models. Common to all these papers is a focus on a small set of predictors based on theoretical models. From an academic viewpoint, the use of model-based predictors facilitates an understanding of specific aspects of the economic mechanism. The benchmark model is historical average equity returns. The alternative models are linear predictive model and two nonparametric predictive models. We find that the combined forecast methods outperform the individual forecast methods. Fama and French (1989) and others show that these variables can detect changes in economic conditions that potentially signal fluctuations in the equity risk premium. But the dividend yield or term spread alone could capture different components of business conditions, and a given individual economic variable may give a number of "false signals" and/or imply an implausible equity risk premium during certain periods. Rapach, Strauss, and Zhou (2009) argue that if individual forecasts based on the predictors are weakly correlated, forecast combinatio should be less volatile and more reliably track movements in the equity risk premium. Our results are consistent with their argument that the combined forecast methods outperform the individual forecast methods. Combining forecast incorporates information from a host of economic variables while the historical average ignores economic variables. Combined forecasts have a substantially smaller bias than the historical average. Combining individual forecasts helps to reduce forecast variability.

The other important results we get are that our nonparametric predictive models have lower RMSE than the historical mean model at both short-horizon and long-horizon. Our nonparametric prediction can improve the out-of-sample performance without restrictions. Using our nonparametric methods, both combined and individual forecast outperform the historical average. One reasonable explanation is that the nonparametric predictive model can fit the equity return better based on the predictors. It is not restricted to the parametric forms. It can fit the data better than simply the linear or nonlinear parametric model. Nonparametric prediction generates a forecast with a variance near that of the smooth real equity return data, thereby reducing the noise in the individual predictive regression model forecasts.

This paper is organized as follows. Section 2 introduces the proposed nonparametric predictability test. Section 3 describes the data. Section 4 presents and discusses the empirical results. Section 5 reports the out-of-sample performance of the individual and combined forecast and economic implication. Section 6 concludes the paper.

2.2 NONPARAMETRIC TEST FOR PREDICTABILITY

2.2.1 Hypotheses of Interests and Nonparametric Test

We are interested in whether the predictability of excess returns depends on time horizons. If future excess returns cannot be predicted by past dividend yield or other variables over any time horizon, then the null hypothesis holds.

Specifically, suppose $\{Y_t, X_t'\}'$ is a stationary time series process where Y_t is a scalar, and X_t is a d-dimensional vector. We are interested in testing the predictability of Y_{t+h} using X_t, where the integer h is the time horizon index for a multi-step ahead prediction. In our applications below, X_t is, for example, the dividend yield in period t, and Y_{t+h} is the asset return h periods ahead. Different h's will allow us to examine the relationship between asset return predictability and time horizons. The null hypothesis of interest can be written as

$$H_0 : E(Y_{t+h}|X_t) = E(Y_{t+h}) \tag{2.2.1}$$

versus the alternative hypothesis

$$H_A : E(Y_{t+h}|X_t) \neq E(Y_{t+h}). \tag{2.2.2}$$

The null hypothesis H_0 is characterized by the horizon index h. It is possible that H_0 holds for a relatively long horizon but it does not hold for a relatively short horizon. This is one of our focuses in this paper, namely we will investigate the relationship between predictability of excess asset returns and the time horizon h, which has been a long-standing problem in empirical finance.

In empirical finance, often a linear predictive regression model

$$Y_{t+h} = X_t'\beta + \varepsilon_{t+h}, \tag{2.2.3}$$

is used to check predictability of excess asset returns. When an estimator for β is statistically insignificant, one does not find evidence for predictability power of X_t for Y_{t+h}. Strictly speaking, one cannot conclude that H_0 holds. This is because a zero parameter value for β is a necessary condition for H_0 but it is not a sufficient condition. A zero β implies that there is no linear predictive power of X_t for Y_{t+h}, but there may exist a nonlinear predictive power of X_t for Y_{t+h}. An example is that the true data generating process follows $Y_{t+h} = X_t^2 + \varepsilon_{t+h}$, where X_t is normally distributed with zero mean and the disturbance ε_{t+h} is independent of X_t. In this case, a linear regression coefficient β is exactly zero but $E(Y_{t+h}|X_t) = X_t^2$.

When an estimator for β is statistically significant, there exists evidence of the predictive power of X_t for Y_{t+h}. In this case, one may be interested in testing whether the linear regression model has the optimal predictive power for Y_{t+h}. Put it differently, one may be interested in testing whether there exists any nonlinear predictive power of X_t for Y_{t+h}, in addition to the documented linear predictability. In this case, the null hypothesis of interest

$$H_0 : E(\varepsilon_{t+h}|X_t) = 0 \tag{2.2.4}$$

versus the alternative hypothesis

$$H_A : E(\varepsilon_{t+h}|X_t) \neq 0, \tag{2.2.5}$$

where ε_{t+h} is the prediction error from the linear regression model in (2.2.3). The null hypothesis H_0 in (2.2.4) implies that the linear regression model in (2.2.3) has optimal predictive power. When H_A in (2.2.5) holds, there exists a nonlinear predictive relationship between X_t and Y_{t+h}, and a suitable nonlinear predictive model will outperform the linear regression model in (2.2.3). Because ε_{t+h} is unobservable, we need to use an estimated residual $\hat{\varepsilon}_{t+h} = Y_{t+h} - X_t'\hat{\beta}$, where $\hat{\beta}$ is an estimator for β. Note that when H_0 holds, $\{\varepsilon_{t+h}\}$ may not be a martingale difference sequence unless $h = 1$. In general, H_0 allows $\{\epsilon_{t+h}\}$ to follow a MA(h) dependence. This has an important implication on inference, particularly when h is relatively large.

In this section, we develop a unified nonparametric testing framework which is applicable to test hypotheses in (2.2.1) and (2.2.4). The basic idea is to use a nonparametric estimator for $E(Y_{t+h}|X_t)$ or $E(\varepsilon_{t+h}|X_t)$ and check if the estimator is close to constant or zero. As is well-known, the nonparametric method has an advantage that it does not require an ex ante model specification and can capture any predictive relationship no matter whether it is linear or nonlinear (c.f. Härdle (1993), Pagan and Ullah (1999)). Thus, it is quite suitable for our purpose here.

To avoid capturing spurious predictability due to in-sample overfitting, we consider out-of-sample predictability check. There are several important reasons why out-of-sample predictability check is important. First, the usual practice of extensive search for more complicated models using the same or similar data set may suffer from the so-called data snooping bias, as pointed out by Lo and MacKinlay (1989) and White (2000). A more complicated model may overfit some idiosyncratic features of the data without capturing the true data generating process. Out-of-sample prediction evaluation will alleviate, if not eliminate completely, such data snooping bias. Second, a model that fits in-sample data well may not predict the future well because of unforeseen structural changes or regime shifts in the data generating process. Therefore, in-sample analysis is not adequate and it is important to examine out-of-sample prediction. Third, out-of-sample prediction is more relevant to most economic applications in practice.

Specifically, suppose we have an observed sample $\{Y_t, X_t'\}_{t=1}^T$ of size T. We first split the sample into two parts: the first subsample contains R observations, and the second subsample contains $n = T - R$ observations. We will use the first subsample or a modification of it to estimate model parameter β and use the second subsample to check predictability. There are various methods to estimate parameter β. One simple method is to use the first subsample $\{Y_{t+h}, X_t'\}_{t=1}^R$ to estimate β. Another method is to use $\{Y_{t+h}, X_t\}_{t=i+1}^{R+i}$ to estimate β when predicting $Y_{R+h+1+i}$, for $0 \leq i \leq n-h-1$. This is called the rolling estimation. One can also use the recursive estimation method, which uses the subsample $\{Y_{t+h}, X_t\}_{t=1}^{R+i}$ to estimate β when predicting $Y_{R+h+1+i}$. Generally, we use the notation $\hat{\beta}_t$ to denote an estimator for β when predicting Y_{t+h} in an out-of-sample context. The resulting estimated out-of-sample residual from a linear model (2.2.3) is

$$\hat{\varepsilon}_{t+h} = Y_{t+h} - X_t'\hat{\beta}_t, t = R+1, \cdots T-h$$

To capture potentially neglected nonlinear predictable component in ε_{t+h}, we use a smoothed kernel method to estimate $E(\varepsilon_{t+h}|X_t)$. Put

$$\begin{aligned} \widehat{m}_h(x) &= \frac{1}{n-h}\sum_{s=R+1}^{T-h} \hat{\varepsilon}_{s+h} K_b(x - X_s), \\ \widehat{g}(x) &= \frac{1}{n-h}\sum_{s=R+1}^{T-h} K_b(x - X_s), \end{aligned}$$

where $x = (x_1, x_2, \cdots, x_d)'$, $y = (y_1, y_2, \cdots, y_d)'$, and $K_b(x-y) = \prod_{i=1}^{d} b^{-1}K[(x_i - y_i)/b]$. The kernel function $K(\cdot)$ is is a prespecified symmetric probability density function. Examples include a Gaussian kernel $K(u) = (2\pi)^{-1/2}\exp(-u^2/2)$ and a quatic kernel $K(u) = \frac{3}{4}(1-u^2)\mathbf{1}(|u| \leq 1)$, where $\mathbf{1}(\cdot)$ is the indicator function, giving value 1 if $|u| \leq 1$ and value 0 otherwise. The bandwidth $b = b(n)$ vanishes to zero as the sample size $n \to \infty$, but at a slower rate. For simplicity, we use the same bandwidth for each components of X_t. In practice, one can first standardize each component of the vector X_t by its sample standard deviation. The regression estimator for $E(\varepsilon_{t+h}|X_t)$ is then defined as follows:

$$\widehat{r}_h(x) = \frac{\widehat{m}_h(x)}{\widehat{g}(x)}.$$

This is called the Nadaraya-Watson regression estimator. The estimator $\widehat{g}(x)$ in the denominator is a kernel estimator for the marginal density $g(x)$ of $\{X_t\}$. Under regularity conditions, $\widehat{r}_h(x) \to r_h(x) = E(\varepsilon_{t+h}|X_t = x)$ in probability as both $R, n \to \infty$.

Under H_0, $\widehat{r}_h(x)$ is close to zero for all x. Under the alternative hypothesis H_A, $\hat{r}_h(x)$ is not a zero function but is a nontrivial function of x subject to sampling variation. To measure the departure of $\hat{r}_h(x)$ from zero over all x, we use the following global measure

$$\widehat{Q}(h) = \frac{1}{n-h} \sum_{t=R+1}^{T-h} \widehat{r}_h^2(X_t) w(X_t),$$

where the positive weighting function $w(\cdot)$ can be chosen to trim the extreme observations where the estimation of $\hat{r}(x)$ is not reliable due to sparse observations (we allow the distribution of X_t has unbounded support). It can also be used to direct power of the proposed test to the region of interest, such as predictability when X_t is negative (in this case, we choose $w(x) = \mathbf{1}(x \leq 0)$. The statistic $\widehat{Q}(h)$ can be viewed as a measure of the magnitude of the "signal" that can be extracted to predict asset returns if (and only if) it contains no systematic predictable component in $E(\varepsilon_{t+h}|X_t)$, the estimator $\widehat{r}_h(X_t)$ and therefore $\widehat{Q}(h)$ will be close to zero.

Alternatively, we can directly use an integrated global measure

$$\widetilde{Q}(h) = \int \widehat{r}_h^2(x)\widehat{g}(x)w(x)dx$$

where the integral is over the support of $w(x)$, and it can be computed using either a numerical integration method (e.g. Gauss-Newton method) or a Monte Carlo simulation method[10].

The asymptotic behaviors of $\widehat{Q}(h)$ and $\widetilde{Q}(h)$ are similar. We now consider the

[10] The Monte Carlo method can be implemented as follows. Without loss of generality assume that $w(\cdot)$ is a prespecified probability density function.Then we can generate a large $i.i.d.$ sample $\{X_i^*\}_{i=1}^N$ from the probability distribution $w(\cdot)$. Then the average $\widehat{Q}^*(h) = N^{-1}\sum_{i=1}^{N}\widehat{r}_h^2(X_i^*)$ will be arbitrarily close to $\widehat{Q}(h)$ if N is sufficiently large (much larger than the sample size n) by the law of large numbers.

decomposition

$$
\begin{aligned}
\widehat{Q}(h) &= \int \widehat{r}_h^2(x)\widehat{g}(x)w(x)dx \\
&= \int \frac{\widehat{m}_h^2(x)}{g(x)}w(x)dx + \int \widehat{m}_h^2(x)\left[\frac{1}{\widehat{g}(x)} - \frac{1}{g(x)}\right]w(x)dx \\
&= \int \widehat{m}_h^2(x)a(x)dx + O_p((Tb)^{-1} + (Tb)^{-\frac{1}{2}} + h^2),
\end{aligned}
$$

where $a(x) = w(x)/g(x)$, and the reminder term is dominated by the first (leading) term under suitable regularity conditions. Thus, we focus on the first term, which will determine the asymptotic distribution of the statistic $\widehat{Q}(h)$.

For the first term, we have

$$
\begin{aligned}
\int \widehat{m}_h^2(x)a(x)dx &= \int \left[\frac{1}{n-h}\sum_{s=R+1}^{T-h} \hat{\varepsilon}_{s+h}K_b(x-X_s)\right]^2 a(x)dx \\
&= \frac{1}{(n-h)^2}\sum_{|t-s|>h} \hat{\varepsilon}_{t+h}\hat{\varepsilon}_{s+h}\int K_b(x-X_t)K_b(x-X_s)a(x)dx \\
&\quad + \frac{1}{(n-h)^2}\sum_{|t-s|\le h} \hat{\varepsilon}_{t+h}\hat{\varepsilon}_{s+h}\int K_b(x-X_t)K_b(x-X_s)a(x)dx \\
&= \widehat{A}(h) + \widehat{B}(h),
\end{aligned}
$$

where the term $\hat{A}(h)$ is a sum over (t,s) with $|t-s| > h$, and the term $\hat{B}(h)$ is a sum over (t,s) with $|t-s| \le h$. For the term $\hat{B}(h)$, we have

$$
\begin{aligned}
\widehat{B}(h) &= \frac{1}{(n-h)^2}\sum_{|t-s|\le h} \hat{\varepsilon}_{t+h}\hat{\varepsilon}_{s+h}\int K_b(x-X_t)K_b(x-X_s)a(x)dx \\
&= \frac{1}{(n-h)^2}\sum_{t=R+1}^{T-h} \hat{\varepsilon}_{t+h}^2 \int K_b^2(x-X_t)a(x)dx \\
&\quad + \frac{2}{(n-h)^2}\sum_{t=R+2}^{n-h}\sum_{s=\max(R+1,t-h)}^{t-1} \hat{\varepsilon}_{t+h}\hat{\varepsilon}_{s+h}\int K_b(x-X_t)K_b(x-X_s)a(x)dx \\
&= \frac{1}{(n-h)b}\sigma_\varepsilon^2 \int w(x)dx \int K^2(u)du + \\
&\quad \frac{2}{(n-h)}\sum_{j=1}^{h}\gamma(j)E[a(X_t)f_j(X_t,X_t)] + O_p((nb)^{-1}),
\end{aligned}
$$

where $\sigma_\varepsilon^2 = var(\varepsilon_{t+h})$, $\gamma(j) = cov(\varepsilon_t, \varepsilon_{t-j})$ is the autocovariance function of $\{\varepsilon_t\}$, and $f_j(\cdot,\cdot)$ is the joint probability density of (X_t, X_{t-j}). Note that generally $\gamma(j) \neq 0$ for $0 \leq j \leq h$ in a h-step ahead prediction model (2.2.3), even when H_0 holds. As noted earlier, $\{\varepsilon_{t+h}\}$ generally displays a MA$(h-1)$ structure under H_0.

Thus, $\hat{B}(h)$ depends on the serial dependence of $\{\varepsilon_{t+h}\}$ due to the existence of the second term. The effect of serial dependence in $\{\varepsilon_{t+h}\}$ on $\widehat{B}(h)$ is generally larger when the horizon parameter h is larger. In our construction of a test statistic, we could subtract the original form of $\hat{B}(h)$ directly from the global measure $\widehat{Q}(h)$, rather than use the asymptotic approximation of $\hat{B}(h)$. This will make the proposed test robust to the effect of serial dependence contained in $\hat{B}(h)$.

The term $\hat{A}(h)$ can be written as

$$\widehat{A}(h) = \frac{2}{(n-h)^2} \sum_{t=R+2}^{n-h} \sum_{s=R+1}^{t-h-1} \hat{\varepsilon}_{t+h} \hat{\varepsilon}_{s+h} \int K_b(x - X_t) K_b(x - X_s) a(x) dx.$$

Under H_0, $\widehat{A}(h)$ has an approximately zero mean. Its variance $var(\widehat{A}(h))$ depends on serial dependence in $\{\varepsilon_{t+h}\}$. However, when $\{\varepsilon_{t+h}\}$ has a MA$(h-1)$ structure where h is a fixed integer, the effect of serial dependence in $\{\varepsilon_t\}$ on $var[\widehat{A}(h)]$ is an asymptotically negligible higher order term, and it can be shown that the asymptotic variance of $b^{d/2}(n-h)\hat{A}(h)/\sigma_\varepsilon^2$ is given by

$$V = 8 \int w^2(x) dx \int \left[\int K(u) K(u+v) du \right]^2 dv.$$

Using the central limit theorem for degenerate U-statistics, we can show $b^{\frac{d}{2}}(n-h)\widehat{A}(h)/\sigma_\varepsilon^2 \xrightarrow{d} N(0, V)$, as stated below:

Theorem 1 *Suppose Assumptions A.1–A.6 in the Appendix hold. Then*

(*i*) *under H_0, we have*

$$\hat{\mathbf{Q}}_h = \frac{\sqrt{b^d}(n-h)\hat{Q}(h)/\widehat{\sigma}_\varepsilon^2 - C/\sqrt{b^d}}{\sqrt{V}} \xrightarrow{d} N(0,1)$$

where $C = \int w(x)dx \int K^2(u)du$, $\widehat{\sigma}_\varepsilon^2 = (n-h)^{-1} \sum_{t=R+1}^{T-h} e_{t+h}^2$, *and* $e_{t+h} = \widehat{\varepsilon}_{t+h} - \widehat{r}_h(X_t)$.

(ii) under H_A,

$$\frac{\hat{\mathbf{Q}}_h}{\sqrt{b^d}(n-h)} \rightarrow \frac{V^{-1/2} \int r_h^2(x)g(x)w(x)dx}{\sigma_\varepsilon^2}.$$

The $\hat{\mathbf{Q}}_h$ test statistic has an appealing interpretation. Ignoring the centering and scaling factors, the $\hat{\mathbf{Q}}_h$ test statistic is essentially based on the ratio $\hat{Q}(h)/\widehat{\sigma}_\varepsilon^2$. Here, the denominator $\widehat{\sigma}_\varepsilon^2$ is the sample variance of pricing errors, and the numerator $\hat{Q}(h)$ is the average of the squared predictable components neglected by the linear regression model (2.2.3). Therefore, the ratio $\hat{Q}(h)/\widehat{\sigma}_\varepsilon^2$ can be viewed as an estimator for the neglected signal-to-noise ratio of the linear model. If the neglected pricing signal $\hat{Q}(h)$ is weak relative to the pricing noise $\widehat{\sigma}_\varepsilon^2$, the $\hat{\mathbf{Q}}_h$ test will not reject the null hypothesis H_0. If the neglected pricing signal $\hat{Q}(h)$ is sufficiently large relative to the pricing noise $\widehat{\sigma}_\varepsilon^2$, the $\hat{\mathbf{Q}}_h$ test will reject the null hypothesis H_0. How large the signal-to-noise ratio should be in order to be considered as sufficiently large is determined by the critical value of the test statistic.

Theorem 1(ii) shows that under H_A, the $\hat{\mathbf{Q}}_h$ statistic diverges to infinity at rate $\sqrt{b^d}(n-h)$. Thus, as long as $r_h(x)$ is not zero over the support of the weighting function $w(x)$ under H_A , the $\hat{\mathbf{Q}}_h$ test will be able to reject H_0 at any given significant level with probability approaching one as the sample sizes $R, n \rightarrow \infty$.

In computing the neglected pricing signal-to-noise ratio, we have used a nonparametric estimator for σ_ε^2. The variance estimator $\widehat{\sigma}_\varepsilon^2$ is based on the nonparametric residual e_{t+h} which is always consistent for the true pricing error $\varepsilon_t^o \equiv Y_{t+h} - E(Y_{t+h}|X_t)$ under both H_0 and H_A. One could also use the parametric variance estimator $\widetilde{\sigma}_\varepsilon^2 = \frac{1}{n-h} \sum_{t=R+1}^{T-h} \widehat{\varepsilon}_{t+h}^2$ using the estimated residuals from the linear regression model. This estimator is simpler than $\widehat{\sigma}_{\varepsilon}^{2}$, and may give better sizes in finite samples, because it is a better estimator for σ_{ε}^{2} than $\widehat{\sigma}_{\varepsilon}^{2}$ under H_0. However, $\widetilde{\sigma}_{\varepsilon}^{2}$ is not consistent for the true error variance $Var(\varepsilon_t^o)$ under H_A, because it contains the neglected signals. Consequently, it may give a lower power in finite samples.

The test statistic $\hat{\mathbf{Q}}_h$ is constructed to check out-of-sample predictability of residual $\hat{\varepsilon}_{t+h}$ using X_t. It can also be used to test the null hypothesis H_0 in (2.2.1), namely the predictability of X_t for Y_{t+h}. This can be done by replacing the sample size n with T, and replacing the estimated residual $\hat{\varepsilon}_{t+h}$ with $Y_{t+h} - \bar{Y}$, where $\bar{Y} = (T-h)^{-1}\sum_{t=1}^{T-h} Y_{t+h}$ is the sample mean of $\{Y_{t+h}\}_{t=1}^{T-h}$. The resulting test statistic is still asymptotically N(0,1) under H_0 in (2.2.1).

Theorem 1(i) implies that approximately $\gamma(n-h)\hat{Q}(h)/\hat{\sigma}_{\varepsilon}^{2} \sim \chi_{\lambda_n}^{2}$ as $R, n \to \infty$ where the constant $\gamma = 2C/V$ and the degree of freedom $\lambda_n = 2C^2/bV$. Here, both constants γ and λ_n do not depend on any nuisance parameters or nuisance functions, such as the error distribution and the density function of X_t. In fact, they are independent of the data generating process. Therefore, the asymptotic null distribution of the scaled signal-to-noise ratio statistic $\gamma(n-h)\hat{Q}(h)/\hat{\sigma}_{\varepsilon}^{2}$ is independent of nuisance parameters or nuisance functions, and approximately $\gamma(n-h)\hat{Q}(h)/\hat{\sigma}_{\varepsilon}^{2}$ is distributed as $N(\lambda_n, 2\lambda_n)$ where λ_n is known. This is the so-called Wilks' phenomena in statistics. One important implication of Wilks' phenomena is that one can simply simulate the null distributions by setting the nuisance parameters under the null hypothesis at reasonable values or estimates.

The asymptotic normality is quite convenient to use in practice. However, several reasons suggest that the asymptotic normal approximation may not work well in finite samples. First, the nonparametric estimator $\widehat{r}_h(x)$ converges slowly to the true function $r_h(x)$ particularly when the dimension d of X_t is relatively large. As it turns out, the neglected reminder terms in the asymptotic expansion of $\hat{Q}(h)/\widehat{\sigma}_\varepsilon^2$ are quite close to in order of magnitude to the dominating term which determines the asymptotic normal distribution of $\hat{\mathbf{Q}}_h$. Evidence in related literature shows that the size of nonparametric test statistics is generally very poor in finite samples. Second, in the present framework, $\{\varepsilon_{t+h}\}$ is not an i.i.d. or martingale difference sequence under the null hypothesis. Instead, it follows an MA$(h-1)$ structure in ε_{t+h} under the null hypothesis H_0 due to the h-step ahead prediction. Asymptotic analysis shows that the serial dependence in $\{\varepsilon_{t+h}\}$ has no impact on the asymptotic mean $C/\sqrt{b^d}$and the asymptotic variance V, but it may substantially affect the finite sample mean and variance of the test statistic $\hat{Q}(h)/\widehat{\sigma}_\varepsilon^2$, particularly when h is relatively large. Third, our asymptotic analysis shows that parameter estimation uncertainty in $\hat{\beta}_t$ has an asymptotically negligible impact on the asymptotic distribution of the proposed test, but the impact depends on the relative magnitude between two sample sizes R, n. When the ratio n/R is large (i.e., when n is large relative to R) , the impact of parameter estimation uncertainty of $\hat{\beta}_t$ may be substantial in finite samples.[11]

2.2.2 Simulation Design and Monte Carlo Evidence

It is well-known that for inference procedures based on linear prediction models, there exist two well-documented sources of size distortion that may arise in long-horizon regressions. First, many predictors, such as dividends and earning price ratios, interest rates, and forward premia, are highly persistent and only predetermined, rather than fully exogenous. Second, standard test-statistics based on prediction regressions do not have their usual limiting distribution (Cavanagh et

[11] One implication of this result is that one should use a large R relative to n in practice to alleviate the impact of parameter estimation in $\widehat{\beta}$.

al., 1995). The use of standard critical values is known to generate severe size distortion. These problems may carry over to the proposed nonparametric predictability test, particularly when h is large. In order to check the reliability of the proposed test, we investigate the finite performance (both size and power) of the proposed test using data-generating processes that could potentially be employed to capture the persistent behavior commonly observed in predictive regressors.

To obtain a reliable reference based on the proposed test in finite samples, we propose the following conditional bootstrap procedure which preserves the MA(h) structure in ε_{t+h} among other things:

Step 1: Use the first subsample $\{Y_{t+h}, X_t'\}_{t=1}^{R}$ to estimate the linear regression model

$$Y_{t+h} = X_t'\beta + \varepsilon_{t+h}, t = 1, ..., R.$$

Obtain the parameter estimator $\hat{\beta}$. Alternatively, rolling estimation or recursive estimation could also be used.

Step 2: Use $\hat{\beta}$ to compute the out-of-sample estimated residual $\hat{\varepsilon}_{t+h} = Y_t - X_t'\hat{\beta}$ for $t = R + 1, ..., T - h$.

Step 3: Compute the nonparametric estimates $\widehat{r}_h(X_t)$ and the nonparametric residual $\widehat{e}_{t+h} = \widehat{\varepsilon}_{t+h} - \widehat{r}_h(X_t)$ for $t = R + 1, ..., T - h$.

Step 4: Compute the signal-to-noise ratio $\hat{Q}(h)/\widehat{\sigma}_{\varepsilon}^2$ using a prespecified kernel $k(\cdot)$ and bandwidth $b = (n - h)^{1/5}$. In practice, data-driven methods can be used to choose the bandwidth b.

Step 5: Estimate an MA($h - 1$) model for the nonparametric residual

$$\widehat{e}_{t+h} = \sum_{j=1}^{h-1} \alpha_j v_{t+h-j} + v_{t+h}, t = R + 1, ..., T - h.$$

This can be done via the conditional quasi-maximum likelihood estimation. Save the moving average parameter estimates $\{\hat{\alpha}_j\}_{j=1}^{h}$ and the estimated residual $\{\hat{v}_{t+h}\}_{t=R+1}^{T-h}$

in the MA$(h-1)$ model.

Step 6: Draw a bootstrap residual sample $\{\hat{v}^*_{t+h}\}_{t=R+1}^{T-h}$ from the centered empirical distribution of $\{\hat{v}_{t+h}\}_{t=R+1}^{T-h}$. Then obtain a bootstrap residual sample $\{\hat{\varepsilon}^*_{t+h}\}_{t=R+1}^{T-h}$ by the following MA$(h-1)$ model

$$\hat{\varepsilon}^*_{t+h} = \sum_{j=1}^{h-1} \hat{\alpha}_j \hat{v}^*_{t+h-j} + \hat{v}^*_{t+h}, t = R+1, ..., T-h,$$

where the parameter estimates $\{\hat{\alpha}_j\}_{j=1}^{h}$ are obtained in step 5. The bootstrap residual $\{\hat{\varepsilon}^*_{t+h}\}_{t=R+1}^{T-h}$ approximately preserves the MA$(h-1)$ structure of $\{\varepsilon_{t+h}\}$ under H_0.

Step 7: Use the bootstrap sample $\{\varepsilon^*_{t+h}, X_t\}_{t=R+1}^{T-h}$ to compute the bootstrap signal-to-noise ratio $\hat{Q}^*(h)/\widehat{\sigma}^{*2}_{\varepsilon}$ using the same kernel $k(\cdot)$ and bandwidth b as in Step 4.

Step 8: Repeat Steps 6 and 7 for a total of B times where B is a large number. Denote the obtained B bootstrap test statistics as $\{\hat{Q}^*_l(h)/\widehat{\sigma}^{*2}_{\varepsilon l}\}_{l=1}^{B}$.

Step 9: Compute the bootstrap p-value of the $\hat{\mathbf{Q}}_h$:

$$p^* = \frac{1}{B}\sum_{l=1}^{B} \mathbf{1}\left[\frac{\hat{Q}(h)}{\widehat{\sigma}^2_{\varepsilon}} < \frac{\hat{Q}^*_l(h)}{\widehat{\sigma}^{*2}_{\varepsilon l}}\right],$$

where $\mathbf{1}(\cdot)$ is the indicator function. Reject the null hypothesis H_0 at significance level α if and only if $p^* < \alpha$.

The above resampling approximation is a wild bootstrap. Here, one only need to calculate the signal-to-noise ratio $\hat{Q}(h)/\widehat{\sigma}^2_{\varepsilon}$ using the observed sample and bootstrap samples. There is no need to compute the original test statistic $\hat{\mathbf{Q}}_h$ which involves calculation of centering and scaling parameters. This follows because computing the bootstrap p-value involves ranking $\hat{\mathbf{Q}}_h$ and $\hat{\mathbf{Q}}^*_h$, which is equivalent to ranking the pricing signal-to-noise ratios $\hat{Q}(h)/\widehat{\sigma}^2_{\varepsilon}$ and $\hat{Q}^*(h)/\widehat{\sigma}^{*2}_{\varepsilon}$, given the fact that the centering and scaling factors do not depend on nuisance parameters and the data generating process. This greatly simplifies the computation of the test statistic.

When testing predictability of X_t for Y_{t+h} (i.e., testing H_0 in (3.1)), Steps 1 and 2 are not needed, the nonparametric residual in step 3 is replaced with $\widehat{e}_{t+h} = Y_{t+h} - \bar{Y}$, and the MA$(h-1)$ models in Steps 6 should be changed to the following:

$$Y^*_{t+h} = \overline{Y} + \sum_{j=1}^{h-1} \hat{\alpha}_j v^*_{t+h-j} + v^*_{t+h}, t = 1, ..., T-h.$$

respectively, where $\bar{Y}$ is the sample mean of $\{Y_{t+h}\}_{t=1}^{T-h}$.

We will examine the finite sample performance of the above conditional bootstrap procedure via simulation studies. Table 2.0 summarizes the five data generating processes we use to investigate the empirical size of the tests for both linear and nonlinear predictability check.

Table 2.0 Summary of Simulation DGPs and Predictability Check

The data-generating processes are summarized in the table below, where $\{v_{t+h}\}$ and $\{u_t\}$ are mutually independent and $\varepsilon_{t+h} = \sum_{j=1}^{h} \alpha_j v_{t+h-j} + v_{t+h}$, $v_{t+h} \sim i.i.d.N(0,1)$, $u_t \sim i.i.d.N(0,1)$. Examine the case where $h = 1, 4, 12, 20$. Sample size $T = 250, 500, 1000$.

	DGP	Y_{t+h}	X_t	β_1, β_2, ρ
(1) Linear	$A.0(h)$	$Y_{t+h} = \alpha_0 + \varepsilon_{t+h}$	$X_t = \rho X_{t-1} + u_t$	$(0.1, 0.3, 0.5, 0.7, 0.9)$
	$A.1(h)$	$Y_{t+h} = \beta_0 + \beta_1 X_t + \varepsilon_{t+h}$	$X_t = \rho X_{t-1} + u_t$	$(0.1, 0.3, 0.5, 0.7, 0.9)$
	$A.2(h)$	$Y_{t+h} = \beta_0 + \beta_1 X_t^2 + \varepsilon_{t+h}$	$X_t = \rho X_{t-1} + u_t$	$(0.1, 0.3, 0.5, 0.7, 0.9)$
(2) Nonlinear	$B.0(h)$	$Y_{t+h} = \beta_0 + \beta_1 X_t + \varepsilon_{t+h}$	$X_t = \rho X_{t-1} + u_t$	$(0.1, 0.3, 0.5, 0.7, 0.9)$
	$B.1(h)$	$Y_{t+h} = \beta_0 + \beta_1 X_t + \beta_2 X_t^2 + \varepsilon_{t+h}$	$X_t = \rho X_{t-1} + u_t$	$(0.1, 0.3, 0.5, 0.7, 0.9)$

Under $A.0(h)$, X_t has no predictive power for Y_{t+h}. This allows us to examine the size of the nonparametric test under $H_1 : E(Y_{t+h}|X_t) = E(Y_{t+h})$. Under

$A.1(h)$ and $A.2(h)$, there exist linear and nonlinear (quadratic form) predictability of X_t for Y_{t+h}.This allows us to examine the power of the test under the alternatives. Next, under $B.0(h)$, there is no neglected nonlinear predictability of X_t for Y_{t+h}. This allows us to examine the size of the test for the null hypothesis $H_2 : E(\varepsilon_{t+h}|X_t) = 0$. Under $B.1(h)$, there exists neglected nonlinear predictability, and this allows us to examine the power of the test.

Tables 2.1a, 2.1b, 2.1c, and 2.1d report empirical rejection rates of the test at the 1%, 5%, and 10% nominal levels, for sample sizes of $T = 250, 500, 1000$ and horizons of $h = 1, 4, 12, 20$. The nonparametric test with the bootstrap procedure has quite reasonable sizes in finite samples under both the null hypotheses H_1 and H_2, which are robust to the length h of horizon and to the persistence of regressor X_t (as measured by the large value of the autoregressive coefficient ρ). Moreover, the proposed test has power under various alternatives to H_1 and H_2 respectively.

The reasonable and robust size and power performance of the proposed test is quite encouraging in view of the fact that due to both long-horizon returns and persistence of the regressors, there is an upward bias in the predictive coefficient on the regressors (Stambaugh 1999, Amihud and Hurvich 2004, Lewellen 2004), and existing long-horizon tests with robust Newey-West standard errors suffer from substantial overrejection.[12]

[12] Ang and Bekaert (2007) point out that the univariate dividend yield regression displays negligible size distortions in the shortest sample for the one-quarter horizon, but for the bivariate regressions, all tests slightly over-reject at asymptotic critical values with longer horizons.

2.3 DATA AND LONG-HORIZON PREDICTABILITY REGRESSION

2.3.1 The long-horizon framework and Predictability Regression

Denote the gross return on equity by $G_{t+1} = (P_{t+1} + D_{t+1})/P_{t+1}$ and the continuously compounded return by $\widetilde{y}_{t+1} = log(G_{t+1})$. The long-horizon predictability regression considered is

$$Y_{t+h} = \alpha_h + \beta_h' X_t + \varepsilon_{h,t+h} \tag{2.3.1}$$

where $Y_{t+h} = (\tau/h)[(\widetilde{y}_{t+1} - r_t) + \cdots + (\ \widetilde{y}_{t+h} - r_{t+h-1})$ is the annualized h-period excess return for the aggregate stock market, r_t is the risk-free rate from t to $t+1$, and $\widetilde{y}_{t+1} - r_t$ is the one period excess return from time t to $t+1$. The constant τ is different, depending on the frequency of the data, i.e., $\tau = 1$ (annually), $\tau = 4$ (quarterly), and $\tau = 12$ (monthly). All returns are continuously compounded.

The error term $\varepsilon_{h,t+h}$ follows a $MA(h-1)$ process under the null hypothesis of no predictability $H_0 : E(Y_{t+h}|X_t) = E(Y_{t+h})$ and $H_0 : E(\varepsilon_{t+h}|X_t) = 0$. We will use different predictors as instruments in X_t, which are explained in details below. We estimate the regression (2.3.1) by OLS and compute standard errors of the parameters using the Newey and West(1987) and Hodrick (1992) standard error formula[13]. We use the test proposed in section 2.2 to check the predictability of different variables using the regression framework in (2.3.1).

2.3.2 Data

We will examine predictability for the equity returns by using data with different frequencies: annual, quarterly, and monthly. The most prominent X_t variables

[13] Using generalized method of moments, (GMM) has an asymptotic distribution $\sqrt{T}(\widehat{\theta} - \theta) \overset{a}{\sim} N(0, \Omega)$ where $\Omega = Z_0^{-1} S_0 Z_0^{-1}$, $Z_0 = E(x_t' x_t)$, and $x_t = (1\ z_t')'$. Hodrick(1992) sums $x_t' x_{t-j}$ into the past and estimates S_0 by $\widehat{S}_0 = \frac{1}{T}\sum_{t=h}^{T} wh_t wh_t'$, $wh_t = \varepsilon_{1,t+1}\sum_{i=0}^{h-1} x_{t-i}$.

considered in the literature are dividend price ratio and dividend yield, earnings yield and dividend-earnings (payout) ratio, various interest rates and spreads, inflation rates, book-to-market ratio, investment-capital ratio, consumption, wealth, and income ratio (CAY), and aggregate net or equity issuing activity.

Stock Returns: Stock returns used are continuously compounded returns on the S&P 500 index, including dividends. Our quarterly data consist of price return (capital gain only), total returns (capital gain plus dividend), and dividends on the Standard & Poor's Composite Index from March 1936 to December 2001. This data is obtained from the Security Price Index Record, published by Standard & Poor's Statistical Service. For monthly data, we use S&P 500 index returns from January 1970 to December 2006 from CRSP's monthend values. Monthly dividends on the S&P 500 index are from Standard & Poor's Statistical Service. For yearly frequency, we get data from 1872 to 2005 provided in Robert Shiller's personal website.

Risk-free Rate: The risk-free rate from 1920 to 2005 is the T-bill rate. We follow the methods by Goyal and Welch (2007) to estimate T-bill rate prior to the 1920's.[14] For quarterly and monthly data, T-bill rates from 1934 to 2005 are the 3-Month Treasury Bill: the Secondary Market Rate from the economic research data base at the Federal Reserve Bank at St. Louis (FRED).

Dividend Yields, Earnings Yields, and Dividend Payout Ratio: Dividends and Earnings are the twelve-month moving sums of dividends and earnings paid on the S&P 500 index. The data from 1871 to 1970 are available from Robert Shiller's

[14] Commercial paper rates for New York City are from the NBER's Macrohistory data base. These are available from 1871 to 1970. We estimated a regression from 1920 to 1971, which yielded $T - billRate = -0.004 + 0.886 * CommercialPaperRate$, with an R^2 of 95.7% according to Goyal and Welch (2007). Therefore, we instrumented the risk-free rate from 1871 to 1919 with the predicted regression equation. The correlation for the period 1920 to 1971 between the equity premium computed using the actual T-bill rate and that computed using the predicted T-bill rate (using the commercial paper rate) is 99.8%.

website. Quarterly dividends and earnings from 1936 to 2005 and monthly dividends and earnings from 1970 to 2006 are from the S&P Corporation. Dividends and Earnings are summed up over the past year. Monthly or quarterly frequency dividends and earnings are impossible to use because they are dominated by seasonal components. The dividend yield (d/y) is defined as $D_t^4/\ P_t$ with the superscript 4 to denote that it is constructed using dividends summed up over the past year (four quarters), where $D_t^4 = D_t + D_{t+1} + D_{t+2} + D_{t+3}$ represents dividends summed over the past year and P_t is the price level on S&P 500.[15] We also define the monthly dividend yield with a superscript of 12 to indicate that dividends have been summed over the past 12 months using the same method. We also denote log dividend yields as $dy_t^4 = \log(D_t^4/\ P_t)$ for quarterly data and $dy_t^{12} = \log(D_t^{12}/\ P_t)$ for monthly data. We use the similar definitions for log earnings yields for both quarterly and monthly. The Dividend Payout Ratio (d/e) is the difference between the log of dividends and the log of earnings.

Stock Variance (svar): Stock Variance is computed as sum of squared daily returns on the S&P 500. G. William Schwert provided daily returns from 1871 to 1926; data from 1926 to 2005 are from CRSP.

Book to Market Ratio: The Book to Market Ratio (b/m) is the ratio of book value to market value for the Dow Jones Industrial Average.[16] Book values from 1920 to 2005 are from Value Line's website, specifically their Long-Term Perspective Chart of the Dow Jones Industrial Average.

Corporate Issuing Activity: We follow the two measures of corporate issuing activity in Goyal and Welch (2007). Net Equity Expansion ($ntis$) is the ratio

[15] See, e.g., Ball (1978), Campbell (1987), Campbell and Shiller (1988a, 1988b), Campbell and Viceira (2002), Campbell and Yogo (2006), the survey in Cochrane (1997), Fama and French (1988), Hodrick (1992), Lewellen (2004), Menzly, Santos, and Veronesi (2004), and Ang and Bekaert(2007).

[16] See Kothari and Shanken (1997) and Ponti and Schall (1998).

of twelve-month moving sums of net issues by S&P listed stocks divided by the total end-of-year market capitalization of S&P stocks. This dollar amount of net equity issuing activity (IPOs, SEOs, stock repurchases, less dividends) for NYSE listed stocks is computed from the CRSP data as $NetIssue_t = Mcap_t - Mcap_{t-1} \cdot (1 + vwretx_t)$, where $Mcap$ is the total market capitalization, and $vwretx$ is the value weighted return (excluding dividends) on the S&P 500 index. These data are available from 1926 to 2005. The second measure, Percent Equity Issuing ($eqis$), is the ratio of equity issuing activity as a fraction of total issuing activity. This is the variable proposed in Baker and Wurgler (2000).[17] The first equity issuing measure is relative to the aggregate market cap, while the second is relative to the aggregate corporate issuing.

Long Term Yield (lty): The data is from Goyal and Welch (2008). The long-term government bond yield data from 1919 to 1925 is the U.S. Yield On Long-Term United States Bonds series in the NBER's Macrohistory data base. Yields from 1926 to 2005 are from Ibbotson's Stocks, Bonds, Bills and Inflation Yearbook, the same source that provided the *Long Term Rate of Returns (ltr). The Term Spread (tms)* is the difference between the long term yield on government bonds and the T-bill. (See, e.g., Campbell (1987) and Fama and French (1989).)

Corporate Bond Returns: Long-term corporate bond returns from 1926 to 2005 are again from Ibbotson's Stocks, Bonds, Bills and Inflation Yearbook. Corporate Bond Yields on AAA and BAA-rated bonds from 1919 to 2005 are from FRED. The Default Yield Spread (dfy) is the difference between BAA and AAA-rated corporate bond yields. The Default Return Spread (dfr) is the difference between long-term corporate bond and long-term government bond returns. (See, e.g., Fama and French (1989) and Keim and Stambaugh (1986).)

[17] We get the data from http://pages.stern.nyu.edu/ jwurgler/

Inflation ($infl$): Inflation is the Consumer Price Index (All Urban Consumers) from 1919 to 2005 from the Bureau of Labor Statistics.

Investment to Capital Ratio (i/k): The investment to capital ratio is the ratio of aggregate (private nonresidential fixed) investment to aggregate capital for the whole economy.

Consumption, wealth, income ratio (cay): The variable cay is proposed by Lettau and Ludvigson (2001)[18]. Data for cay's construction at quarterly frequency from the second quarter of 1952 to the fourth quarter of 2005 are available from Martin Lettau's website. The annual data from 1948 to 2001 is available from Martin Lettau's website.

Table 2.2 summarizes the descriptive statistics of the predictors. Panels (a), (b), and (c) report the results for quarterly, monthly, and annual data respectively. Short rates, dividend and earnings yields, book-to-market ratio, and inflation are all highly persistent at different frequencies. Because the persistence of these instruments plays a crucial role in the finite sample performance of predictability test statistics, we report test statistics under the null of a unit root. Figure 2.1 plot excess returns, interest rate, dividend yields, and earnings yields from March 1936 to December 2001 quarterly. For annual data, Figure 2.2 and 2.3 plot dividend payout ratio, short rate, inflation, book-to-market ratio, investment to capital ratio(i/k), corporate issuing activity ($eqis$ and $ntis$), and consumption, wealth, and income ratio(cay) from 1872 to 2005 annually.

[18]Lettau and Ludvigson (2001) estimate the following equation: $c_t = \alpha + \beta_a a_t + \beta_y y_t + \sum_{i=-k}^{k} b_{a,i}\Delta a_{t-i} + \sum_{i=-k}^{k} b_{y,i}\Delta y_{t-i} + \epsilon_t$, $t = k+1, ..., T-k$, where c is the aggregate consumption, a is the aggregate wealth, and y is the aggregate income. Using estimated coefficients from the above equation provides $cay = \widehat{cay}t = c_t - \alpha - \widehat{\beta}_a a_t - \widehat{\beta}_y y_t$, $t = 1, ..., T$.

2.4 IS THE PREDICTABILITY THERE?

In this section, we first apply the nonparametric test to examine whether there exists the predictability of equity returns for both short and long horizons. Next, we will use the test to compare the conventional predictive regression models on predictor variables with the historical mean model according to Goyal and Welch (2007) and Campbell and Thompson(2007). Finally we provide a simulation study on the size and power of the proposed test to assess the reliability of the proposed test in finite samples.

2.4.1 Short-Horizon and Long-Horizon Predictability

The main regressions we consider are $Y_{t+h} = \alpha_h + \beta_h' X_t + \varepsilon_{h,t+h}$ in (2.3.1). We use quarterly, monthly, and annual data to check the predictability of equity returns. For quarterly and monthly data, we report results for four sample periods, from 1936 to 2001, from 1952 to 2001, from 1936 to 1990, and from 1952 to 1990, which are the same sample periods considered in Ang and Bekaert (2007).[19]

Table 2.3 summarizes the results on the excess return predictability for horizons of 1 quarter, 1 year, 3 years, and 5 years respectively. Table 2.3a focuses on the univariate regression with log dividend yields or log earnings yields as the regressor. The t-statistics in parentheses are computed using the Newey and West (1987) and Hodrick (1992) standard error formula respectively. The parameter estimates have similar patterns over the 4 periods, but the coefficient estimates are twice as large for the period omitting the 1990s from the sample. The Hodrick standard errors

[19] Interest rate data are hard to interpret before the 1951 Treasury Accord, as the Federal Reserve pegged interest rates during the 1930s and the 1940s. Hence, we examine the post-Accord period, starting in 1952. Second, the majority of studies establishing strong evidence of predictability use data before or up to the early 1990s. Studies by Lettau and Ludvigson (2001) and Goyal and Welch (2003) point out that predictability by the dividend yield is not robust to the addition of the 1990s decade. Hence, we separately consider the effect of adding the 1990s to the sample.

are smaller than the Newey-West standard errors. During the 1936-2001 and 1952-2001 periods, there is no evidence of predictability for dividend yields for both short and long horizons. For the 1936-1990 periods, there is strong predictability for dividend yields over the horizons of 1 quarter, 1 year, 3 years, and 5 years respectively. Yet for the 1952-1990 period, there exists only the predictability for short horizons of 1 quarter and 1 year.

Table 2.3a reports the bootstrap p-value for the predictability test under two hypotheses $H1$ and $H2$. Hypothesis $H1$ is $H_0 : E(Y_{t+h}|X_t) = E(Y_{t+h})$, namely that X_t has no predictive power for Y_{t+h}, and Hypothesis $H2$ is $H_0 : E(\varepsilon_{t+h}|X_t) = 0$, namely that X_t has no neglected nonlinear predictive power for Y_{t+h} beyond the linear model (2.3.1). As mentioned in Section 2.2, the $\hat{\mathbf{Q}}_h$ test has an appealing interpretation: it is essentially based on the ratio $\hat{Q}(h)/\widehat{\sigma}_\varepsilon^2$, where the denominator $\widehat{\sigma}_\varepsilon^2$ is the sample variance of pricing errors, and the numerator $\hat{Q}(h)$ is the average of the squared predictable components neglected by the linear regression model. Therefore, the ratio $\hat{Q}(h)/\widehat{\sigma}_\varepsilon^2$ can be viewed as an estimator for the neglected signal-to-noise ratio of the linear prediction model (2.3.1). If the neglected pricing signal $\hat{Q}(h)$ is weak relative to the pricing noise $\widehat{\sigma}_\varepsilon^2$, the $\hat{\mathbf{Q}}_h$ test will not reject the null hypothesis H_0. If the neglected pricing signal $\hat{Q}(h)$ is strong relative to the pricing noise $\widehat{\sigma}_\varepsilon^2$, the $\hat{\mathbf{Q}}_h$ test will reject the null hypothesis H_0. The results for testing $H1$ show that the $\hat{\mathbf{Q}}_h$ test strongly rejects the null hypothesis $H1$ for dividend yields over the 4 sample periods. This implies that dividend yield is a significant predictor of excess returns at all horizons, which is consistent with the prevailing result found by Campbell and Shiller (1988a,b).

Next, we examine whether there exists neglected nonlinear predictability of dividend yield. Table 2.3a show that the $\hat{\mathbf{Q}}_h$ test strongly rejects the null hypothesis

$H2$ for all 4 sample periods. Thus, there exists a nonlinear predictive relationship between X_t and Y_{t+h}, and a suitable nonlinear predictive model is expected to outperform the linear regression model.

The right four columns of Table 2.3a also report a univariate regression with the earnings yield as the regressor. The results suggest that there is no strong evidence for linear predictability of earnings yields over 4 sample periods. The nonparametric tests for hypothesis $H1$ and $H2$, however, show that earnings yield is a good predictor for equity returns over all the horizons.

Table 2.3b summarizes the bivariate regression with log dividend yields and short rate together as regressors. The t-statistics in parentheses are computed using the Newey and West (1987) and Hodrick (1992) standard error formula. Horizons h are quarterly. Table 2.3b also reports the bootstrap p-value for the predictability test for six various hypotheses $H1 - H6$, where X_1 represents the short rate r and X_2 the dividend yield. The six Hypotheses are, respectively, $H1$ ($H_0 : E(Y_{t+h}|X_{1t}) = E(Y_{t+h})$), $H2$ ($H_0 : E(\varepsilon_{t+h}|X_{1t}) = 0$), $H3$ ($H_0 : E(Y_{t+h}|X_{1t}) = E(Y_{t+h})$), $H4$ ($H_0 : E(\varepsilon_{t+h}|X_{2t}) = 0$), $H5$ ($H_0 : E(Y_{t+h}|X_{1t}, X_{2t}) = E(Y_{t+h})$), and $H6$ ($H_0 : E(\varepsilon_{t+h}|X_{1t}, X_{2t}) = 0$). Hypotheses $H1$ and $H2$ are on predictability of the short rate or dividend yield separately and Hypothesis $H5$ is on the joint predictability of the short rate and dividend yield together. The results based the Newey-West standard errors suggest that the short rate has strong predictability over the 4 periods but the predictability only exists at short horizons when using the Hodrick (1992) standard errors. In the bivariate regression, there is evidence of predictability of dividend yields for equity returns when the sample period excludes the 1990s. The coefficient on the dividend yield is larger in the bivariate regression than in the univariate regression. This suggests that the univariate regression suffers from an omitted variable bias that lowers the marginal impact of dividend yields on expected excess returns.[20] The $\hat{\mathbf{Q}}_h$ test significantly rejects the hypotheses $H1 - H4$ for all 4 sample periods, indicating that that the short rate and dividend yield are two good predictors for equity returns which cannot be fully captured by linear prediction regressions.

The $\hat{\mathbf{Q}}_h$ test rejects the hypothesis $H5$ only at the horizon of 1 quarter and fails to reject at the horizons of 1 year, 3 year2, and 5 years for the 1936-2001 period. The $\hat{\mathbf{Q}}_h$ test rejects hypothesis $H5$ for the 1952-2001, 1936-1990, and 1952-1990 periods. These results suggest that there is evidence of joint predictability for the short rate and dividend yield together for the 3 sample periods (1952-2001, 1936-1990, and 1952-1990) and the short rate and dividend yield together have the predictability only at the short horizon of 1 quarter in the 1936-2001 period. The $\hat{\mathbf{Q}}_h$ test rejects hypothesis $H6$ for the 4 time periods with exception for the horizon of 5 years in the 1936-2001 and 1952-1990 periods. The bivariate linear regression does not have the optimal predictive power for equity returns over all the horizons in the 4 time periods. Nevertheless, it may have the long-horizon predictive power for the horizon of 5 years in the 1936-2001 and 1952-1990 periods since there is no strong evidence to reject hypothesis $H6$. Ang and Bekaert (2007) examine the predictive power of dividend yields for forecasting excess returns. They find that dividend yields predict excess returns only at short horizons together with the short rate and do not have any long-horizon predictive power. At short horizons, the short rate strongly negatively predicts returns.

To compare with Lamont (1998) and Ang and Bekaert (2007), we report a bivariate regression of excess returns on log dividend and log earnings yields. Lamont

[20] Engstrom (2003), Menzly, Santos, and Veronesi (2004), and Lettau and Ludvigson (2005) also note that a univariate dividend yield regression may understate the dividend yield's ability to forecast returns.

(1998) finds a positive coefficient on the dividend yield and a negative coefficient on the earnings yield. He argues that the predictive power of the dividend yield stems from the role of dividends in capturing permanent components of prices, whereas the negative coefficient on the earnings yield is due to earnings being a good measure of business conditions. Ang and Bekaert (2007) finds that dividend and earnings yields do not have a strong predictive power and only when the 1990s are excluded they find significant coefficients for dividend and earnings yields. Table 2.3c summarizes the bivariate regression with the log dividend yields and log earnings yields together as regressors. The dividend yields and earnings yields have a strong predictive power for equity returns over the 4 time periods when using the Newey-West (1987) standard errors. The results using the Hodrick (1992) standard errors are similar to Ang and Bekaert (2007). The $\hat{\mathbf{Q}}_h$ test rejects the six hypotheses over all the time horizons and for all 4 time periods. It supports Lamont (1998)'s arguments. Dividend yields and earnings yields have the predictability power for equity returns but the bivariate linear regression model cannot fully capture such predictability.

Table 2.3d summarize the trivariate regression with the short rate, log dividend yields, and log earnings yields together as regressors. When we add the short rate as a predictor in a trivariate regression of excess returns on risk-free rates, dividend and earnings yields, the coefficients on dividend and earnings yields remain insignificantly different from zero, and the sign on the earnings yield is fragile. For the post-1952 samples, the short rate, and dividend yields have predictive power in the presence of the earnings yield. The results for the $\hat{\mathbf{Q}}_h$ test show that the three variables short rate, dividend yields, and earnings yields do have the predictability power for the equity returns. The $\hat{\mathbf{Q}}_h$ test for the joint predictability of the three variables rejects the hypothesis $H7$ for most of the cases except the horizons of 1 year and 3 years in the 1936-2001 and 1936-1990 periods and the horizon of 5 year in the 1952-2001 period. And the trivariate regression does not capture the true equity returns and it needs a better nonlinear model to capture it.

We use the monthly data from January 1970 to December 2006 to test the predictability of the short rate, dividend yields, and earnings yields in univariate, bivariate, and trivariate regressions respectively. Table 2.4 summarizes the results for the regressions and predictability tests. We obtain similar results to those based on quarterly data. Using the Hodrick (1992) standard errors, our results suggest that the short rate has strong predictability. The nonparametric predictability tests show that the three variables are good candidates to predict equity returns but linear predive regression models cannot fully capture such predictability.

2.4.2 Does the prevailing models beat the historical mean?

Goyal and Welch (2007) reexamine the performance of variables that have been suggested by the academic literature to be good predictors of equity premiums. They find that those models have predicted poorly both in-sample and out-of-sample for thirty years and can not beat the historical mean model. We consider both In-Sample (IS) and Out-of-Sample (OOS) tests. Following Goyal and Welch (2007), the OOS forecasts use only the data available up to the time at which the forecast is made. Let e_N denote the vector of rolling OOS errors from the historical mean model and e_A denote the vector of rolling OOS errors from the OLS model. The OOS statistics are computed as $R^2 = 1 - \frac{MSE_A}{MSE_N}$, $\overline{R}^2 = R^2 - (1 - R^2) \cdot (\frac{T-k}{T-1})$, $\Delta RMSE = \sqrt{MSE_N} - \sqrt{MSE_A}$. It is important but difficult for OOS tests to choose the periods over which a regression model is estimated and subsequently evaluated. In this section we consider the annual prediction with similar data used in Goyal and Welch (2007). For the OOS test, we explore the time period specification which begins OOS forecasts twenty years after data are available.

We estimate regressions of form $Y_{t+h} = \alpha_h + \beta_h' X_t + \varepsilon_{h,t+h}$ in (2.3.1), with X_t being log dividend yields, log earnings yields, dividend payout ratio, short rate, inflation, book-to-market ratio(b/m), investment to capital ratio(i/k), corporate issuing activity (Eqis and Ntis), and consumption, wealth, and income ratio(cay). The results are summarized in Table 2.5. The t-statistics in parentheses are computed using the Newey and West (1987) and Hodrick (1992) standard errors. We report the bootstrap p-value for the predictability test under two hypotheses $H1$ and $H2$. Hypothesis $H1$ is $H_0 : E(Y_{t+h}|X_t) = E(Y_{t+h})$ and Hypothesis $H2$ is $H_0 : E(\varepsilon_{t+h}|X_t) = 0$.Table 2.5 summarizes both in-sample and out-of-sample results. To compare the prevailing predictive models with the historical mean model, we introduce a criterion $\Delta(\frac{Q_h}{\sigma^2}) = \hat{Q}_N(h)/\widehat{\sigma}^2_\varepsilon - \hat{Q}_A(h)/\widehat{\sigma}^2_\varepsilon$, where $\hat{Q}_N(h)/\widehat{\sigma}^2_\varepsilon$ and $\hat{Q}_A(h)/\widehat{\sigma}^2_\varepsilon$ are the signa-to-noise ratios of the historical mean model and the prevailing predictive regression model respectively. If $\Delta(\frac{Q_h}{\sigma^2}) > 0$, there is more neglected signal which cannot be explained by the historical mean model and thus the prevail predictive model performs better. If $\Delta(\frac{Q_h}{\sigma^2}) < 0$, there is more neglected signal which cannot be captured by the prevail predictive model and so the historical mean model performs better.

Table 2.5 shows that when a linear prediction model is used, all variables considered are insignificant and only several variables (dividend yield, short rate, eqis, and cay) are significant at the horizon of 1 year using the Newey-West standard errors. However, the results for both in-sample and out-of-sample nonparametric tests show that all variables considered (i.e., log dividend yields, log earnings yields, dividend payout ratio, short rate, inflation, book-to-market ratio(b/m), investment to capital ratio(i/k), corporate issuing activity (Eqis and Ntis), and consumption, wealth, and income ratio(cay)) have predictability power for equity returns. For all the cases considered, $\Delta(\frac{Q_h}{\sigma^2})$ is larger than zero for both in-sample and out-of-sample There exists more neglected signal which cannot be explained by the historical mean model and thus the prevail predictive model performs better. This conclusion differs from Goyal and Welch (2007) and supports Campbell and Thompson (2007).

2.5 OUT-OF-SAMPLE FORECASTING OF EQUITY RETURNS

As mentioned in the previous sections, Goyal and Welch (2008) create enough of a controversy within the profession and argue that the historical average excess stock return forecasts future excess stock returns better than regressions of excess returns on predictor variables. Campbell and Thompson (2008) and Cochrane (2008) soon follow with opposing views. Campbell and Thompson argue that the empirical models can yield useful out-of-sample forecasts if one restricts their parameters in economically justified ways. In contrast, Cochrane (2008) argues that the types of out-of-sample tests performed by Goyal and Welch are relatively weak, and that in-sample tests provide far greater power and can be convincing on their own. The literature emphasizes that the most linear predictive regressions have often performed poorly out-of-sample (Goyal and Welch (2003, 2007); Campbell and Thompson (2007)). The lack of consistent out-of-sample evidence in Goyal and Welch (2008) indicates the need for improved forecasting methods to better establish the empirical reliability of equity premium predictability. Rapach, Strauss, and Zhou (2009) propose a combination approach to improve the out-of-sample equity premium forecasting problem. In this section, we propose a nonparametric estimator to forecast the equity returns.

2.5.1 Nonparametric forecast, linear predictive model, and Historical Mean Model

In the previous sections, our nonparametric test has proved that there exists the predictability of equity returns at short and long horizons. The predictors such as dividend yields, earnings yields, dividend payout ratio, short rate, inflation, book-to-market ratio, investment to capital ratio, corporate issuing activity, and consumption, wealth, and income ratio have predictability power for equity returns, but this often cannot be captured by popular linear regression models. We find that the poor out-of-sample performance of most linear prediction models is due to the limitation of linear models. We need to find the better fit of the equity returns.

Following the section 2.2, we use two nonlinear estimators to forecast the equity returns. The first estimator is to use a smoothed kernel method to estimate $E(\varepsilon_{t+h}|X_t)$ and capture potentially neglected nonlinear predictable component in ε_{t+h}. So the expected equity returns can be defined as follows:

$$\begin{aligned}
E(Y_{t+h}|X_t) &= X_t'\widehat{\beta} + E(\varepsilon_{t+h}|X_t) = X_t'\widehat{\beta} + \widehat{r}_h(x). \\
&= X_t'\widehat{\beta} + \frac{\widehat{m}_h(x)}{\widehat{g}(x)} \\
\widehat{m}_h(x) &= \frac{1}{n-h}\sum_{s=R+1}^{T-h}\hat{\varepsilon}_{s+h}K_b(x - X_s), \\
\widehat{g}(x) &= \frac{1}{n-h}\sum_{s=R+1}^{T-h}K_b(x - X_s)
\end{aligned}$$

where $x = (x_1, x_2, \cdots, x_d)'$, $y = (y_1, y_2, \cdots, y_d)'$, and $K_b(x - y) = \prod_{i=1}^{d} b^{-1}K[(x_i - y_i)/b]$. The kernel function $K(\cdot)$ is is a prespecified symmetric probability density function. The second estimator is to use a smoothed kernel method to estimate

$E(Y_{t+h}|X_t)$ directly. We can predict the equity returns by

$$E(Y_{t+h}|X_t) = \frac{\frac{1}{n-h}\sum_{s=R+1}^{T-h} Y_{s+h}K_b(x-X_s)}{\widehat{g}(x)}$$

We want to compare the out-of-sample forecast results of four models: historical mean model, linear predictive model, and two nonlinear predictive models. The three measures we use are MSE (Mean squared error), MAE (Mean absolute error), and RMSE (Root mean squared error). The smaller the RMSE is and the model has a better fit.

$$\begin{aligned} MSE &= \frac{1}{n-h}\sum_{s=R+1}^{T-h}(Y_{s+h}-\widehat{Y}_{s+h})^2 \\ MAE &= \frac{1}{n-h}\sum_{s=R+1}^{T-h}\left|Y_{s+h}-\widehat{Y}_{s+h}\right| \\ RMSE &= \sqrt{\frac{1}{n-h}\sum_{s=R+1}^{T-h}(Y_{s+h}-\widehat{Y}_{s+h})^2} \end{aligned}$$

Table 2.6 show the out-of-sample results of the univariate linear predictive models. Table 2.6a summarize the MSE, MAE, and RMSE of linear predictive regression for dividend yield and earning yield during the period 1936-2001, and 1952-2001. The benchmark model is historical average equity returns. The alternative models are linear predictive model and two nonparametric predictive models. We find that our second nonparametric predictive model has the lower RMSE than the historical mean model. The linear predictive model and the first nonparametric predictive model have higher RMSE than the historical mean model. The second nonparametric predicitve model can do better job than historical mean model in both short horizon and long horizon. Table 2.6b summarize the MSE, MAE, and RMSE of linear predictive regression for dividend yield and earning yield during the period 1936-1990, and 1952-1990. We find that both first and second nonparametric predictive models have the lower RMSE than the historical mean model. The linear predictive model has higher RMSE than the other three models. The two nonparametric predicitve models can do better job than historical mean model in both short horizon and long horizon.

Table 2.7 reports out-of-sample bivariate regression results with the short rate as an additional regressor. For the period of 1936-2001, 1936-1990, and 1952-1990, the second nonparametric predictive regression model has the smallest RMSE. For the post-Treasury Accord 1952–2001 sample, the linear predictive model and the first nonparametric predictive model has higher RMSE than the historical mean model. The second nonparametric predicitve model can do better job than historical mean model in both short horizon and long horizon. In the bivariate regression with earning yield and short rate, the second nonparametric predictive regression model is superior to the other three models during the period 1936-2001 and 1952-2001. Table 2.7b summarize the statistical results of bivariate linear predictive regression for dividend yield and earning yield by using the measure MSE, MAE, and RMSE during the period 1936-1990, and1952-1990. The linear predictive model has higher RMSE than the other three models. The two nonparametric predicitve models can do better job than historical mean model in both short horizon and long horizon. Ang and Bekaert (2007) find that dividend yields, together with the short rate, predict excess returns only at short horizons. In this section, we find that the nonparametric predictive model can capture the equity returns well and the short rate, dividend yields, and earnings yields have good predictability power at both short and long horizons. The results in the four subsample are consistent and it shows that our nonparametrc predictive models are robust to smooth changes.

Goyal and Welch (2007) argue that the historical average excess stock return forecasts future excess stock returns better than regressions of excess returns on predictor variables. With respect to the economic variables used to predict the equity premium, we consider the 15 variables from Goyal and Welch (2008) for which quarterly data are available for 1947:1–2007:4 and annual data are from 1872 to 2005. They are dividend-price ratio (D/P), dividend yield (D/Y), earnings-price ratio (E/P), dividend-payout ratio (D/E), stock variance ($SVAR$), book-to-market ratio (B/M), net equity expansion ($NTIS$), treasure bill rate (TBL), long-term yield (LTY), long-term return (LTR), term spread (TMS), default yield spread (DFY), default return yield (DFR), inflation ($INFL$), and investment-to-capital ratio (I/K). Common to all these papers is a focus on a small set of predictors based on theoretical models. From an academic viewpoint, the use of model-based predictors facilitates an understanding of specific aspects of the economic mechanism. The benchmark model is historical average equity returns. The alternative models are linear predictive model and two nonparametric predictive models. Table 2.8 report the equity premium out-of-sample forecasting results using the annual data. Consistent with the previous results, the second nonparametric predicitve model can do better job than historical mean model and linear predictive model in both short horizon and longer horizon. Table 2.10 report the equity premium out-of-sample forecasting results using the quarterly data from 1947:1–2007:4. We consider the out-of-sample forecast evaluation periods covering 1965:1–2007:4 consistent with Goyal and Welch (2008). The statistical results show that the second nonparametric predicitve model can do better job than historical mean model and linear predictive model in both short horizon and long horizon. For most predictors except dividend-price ratio (D/P), dividend yield

(D/Y), earnings-price ratio (E/P), and book-to-market ratio (B/M), the two nonparametric models are superior to the historical mean model and linear regression model.

Figure 2.4 and 2.6 illustrate the out-of-sample performance for annual predictive regressions for individual methods. The black dotted line is the real data of the equity returns and the red dotted line is the unconditional historical average. The red and green solid line are the forecasted returns by the first and second nonparametric models respectively. A predictive regression model that always outperforms the historical average for any out-of-sample period will thus have a curve below the historical average curve. For individual predictor-based models, the second nonparametric prediction is mostly below the unconditional historical average line. Even for some periods, the nonparametric method is above the historical average yet on average it outperforms the historical average. Campbell and Thompson (2008) show that imposing theoretically motivated restrictions on individual predictive regression models can improve their out-of-sample performance. We find that our nonparametric prediction can improve the out-of-sample performance without restrictions. Figure 2.8, 2.10 and 2.12 illustrate the out-of-sample performance for quarterly predictive regressions for individual methods over 1-quarter, 1-year, and 3-year rolling windows. We find the similar results for the quarterly data.

2.5.2 Individual Forecast and Combined Forecast

In the literature, most papers focus on a set of predictors based on theoretical models. From an academic viewpoint, the use of model-based predictors facilitates an understanding of specific aspects of the economic mechanism. From an investor's viewpoint, however, these predetermined variables may not be enough to capture all information required in decision making. Forecast combination has recently received renewed attention in the forecasting literature; Stock and Watson (1999, 2003, 2004) with respect to forecasting inflation and real output growth. Rapach, Strauss, and Zhou (2009) propose a combination approach to improve the out-of-sample equity premium forecasting problem. In addition to the individual forecast, we also consider the combined forecast to improve equity premium forecasts, and examine the out-of-sample performance.

We follow the definition of the combined forecast by Rapach, Strauss, and Zhou (2009). The combination forecasts of Y_{t+1} made at time t are weighted averages of the M individual forecasts based on $\widehat{Y}_{c,t+h} = \sum_{i=1}^{M} \omega_{i,t} \widehat{Y}_{i,t+h}$ where $\{\omega_{i,t}\}_{i=1}^{M}$ are the ex ante combining weights formed at time t, and $\widehat{Y}_{i,t+h}$ is the out-of-sample forecast of the equity premium based on the individual predictive models[21]. For the individual predictors, we choose the 15 predictors used in the previous sections. We calculate five different combining methods based on the definition of the weights. The first three methods use simple averaging schemes: mean, median, and trimmed mean. The mean combination forecast sets $w_{i,t} = 1/M$ for $i = 1, \cdots, M$. The median combination forecast is the median of $\{\widehat{Y}_{i,t+h}\}_{i=1}^{M}$, and the trimmed mean combination forecast sets $w_{i,t} = 0$ for the individual forecasts with the smallest and largest values and $w_{i,t} = 1/(M-2)$ for the remaining individual forecasts. The other two combining methods are based on Stock and Watson (2004) and Rapach, Strauss, and Zhou (2009), where the combining weights formed at time t are functions of the historical forecasting performance of the individual models over the holdout out-of-sample period. Their discount mean square prediction error $(DMSPE)$ combining method employs the following weights: $w_{i,t} = \phi_{i,t}^{-1} / \sum_{j=1}^{M} \phi_{j,t}^{-1}$,

[21] $Y_{t+h} = \alpha_h + \beta_h' X_t + \varepsilon_{h,t+h}$

$\phi_{i,t} = \sum_{s=R}^{t-1} \theta^{t-1-s}(Y_{i,t+h} - \widehat{Y}_{i,t+h})^2$ and θ is a discount factor. The DMSPE method thus assigns greater weights to individual predictive regression model forecasts that have lower MSPE values (better forecasting performance) over the holdout out-of-sample period. We consider the two values of 1.0 and 0.9 for θ.

Table 2.9 report the equity premium out-of-sample combined forecasting results using the annual data. Consistent with the previous results, the two nonparametric predicitve models have lower $RMSE$ and can do better job than historical mean model and linear predictive model in both short horizon and long horizon. In addition, using combined method linear predictive model can outperform the historical mean model. Table 2.11 report the equity premium out-of-sample combined forecasting results using the quarterly data from 1947:1–2007:4. We consider the out-of-sample forecast evaluation periods covering 1965:1–2007:4 consistent with Goyal and Welch (2008). The statistical results show that the two nonparametric predicitve models can do better job than historical mean model and linear predictive model in both short horizon and long horizon. Rapach, Strauss, and Zhou (2009) find that forecast combination outperforms the historical mean model by statistically and economically meaningful margins for out-of-sample period. Our results are consistent with their conclusion. Using our nonparametric methods, both combined and individual forecast outperform the historical average. The combined forecast methods outperform the individual forecast methods.

Figure 2.5 and 2.7 illustrate the out-of-sample performance for annual predictive regressions for combined methods. The black dotted line is the real data of the equity returns and the red dotted line is the unconditional historical average. The red and green solid line are the forecasted returns by the first and second nonparametric models respectively. For combined predictor-based models, the two nonparametric prediction models are below the unconditional historical average line. We find that our nonparametric prediction can improve the out-of-sample performance without restrictions. Figure 2.9, 2.11 and 2.13 illustrate the out-of-sample performance for quarterly predictive regressions for combined methods over 1-quarter, 1-year, and 3-year rolling windows. We find the similar results for the quarterly data.

2.5.3 Economic Implication

From the previous two sections, we get two important results: (1) our nonparametric predictive models have lower RMSE than the historical mean model at both short-horizon and long-horizon. Our nonparametric prediction can improve the out-of-sample performance without restrictions. (2) Using our nonparametric methods, both combined and individual forecast outperform the historical average. The combined forecast methods outperform the individual forecast methods. In this section, we investigate how well our nonparametric predictive models capture true expected returns implied by the models.

Predictability over Different Horizons From the empirical results we obtain in the previous sections, we find an interesting phenomenon that the predictability power of equity returns increases when the forecasting horizon h increases. Ang and Bekaert (2007) find that dividend yields, together with the short rate, predict excess returns only at short horizons and do not have any long-horizon predictive power. Goyal and Welch (2008), and Campbell and Thomason (2008) do not find the relationship between the predictability and time horizons. Fama and Schwert (1977), Fama (1981), Keim and Stambaugh (1986), and French, Schwert, and Stambaugh (1987). However, Fama and French (1987a) find that portfolio returns for holding periods beyond a year have strong negative autocorrelation. They show that under some assumptions about the nature of the price process, the autocorrelations imply that time-varying expected returns explain 25-40% of three- to five-year return variances. Using variance-ratio tests, Poterba and Summers (1987) also estimate that long-horizon stock returns have large predictable components. Economic theory has already shown that there exists nonlinear relationship between the predictors such as dividend yield and equity returns. If expected returns have strong positive autocorrelation, rational forecasts of one year returns one to four years ahead are highly correlated. As a consequence, the variance of expected returns grows faster with the return horizon than the variance of unexpected returns. And the variation of expected returns becomes a larger fraction of the variation of returns. In the short run, the nonlineariy is relatively weak. When time accumulates, the nonlinear relationship becomes stronger in the long run. Our nonparametric method has its advantage to detect the nonlinearity. That is why the RMSE becomes smaller when the time horizon h becomes larger. In other words, the linear predictive models can capture nonlinear relationship in the short run better than in the long run. The difference of the RMSE between nonparametric model and linear predictive model is relatively small when forecasting horizon h is small and becomes bigger for the larger forecasting horizon h.

How do we distinguish our nonparametric model with the nonlinear model? Why do we use nonlinear predictive model to detect the nonlinear predictive components? First, the existing economic theory in the literature can not give a concrete form of the nonlinear predictive model because we don't know where the nonlinearity exactly comes from. Second, nonlinear models, such as cubic or quadratic functions, may misspecify the nonlinearity of the true data. There may exist outliers and it will cause the spurious identification for the predictability. Third, nonparametric model can capture the linear and nonlinear component without the model specification. It is not restricted to the parametric forms. It can fit the data more better than simply the linear or nonlinear parametric model. Specifically, our prediction results can be improved by choosing better bandwith. In our paper, we choose the bandwith which is correlated with the size of the out-of-sample forecasting period. We can also use data-driven method to choose the bandwith. It will affect our out-of-sample forecast performance.

Predictability over Different Models and Methods We have the out-of-sample forecasting performance results of equity premium using different frequencies of the data. The first impression of the results is that our nonparametric predictive models do a better job than historical mean model and linear predictive model for the same forecasting horizon h. We find the predictors have the predictability of the equity returns using our nonparametric test and linear predictive regression can not capture the nonlinear component of the true data. We use nonparametric model to predict the equity returns because it can capture the linear and nonlinear component without the model specification. It is not restricted to the parametric forms. It can fit the data more better than simply the linear or nonlinear parametric model.

According to our nonparametric testing results, the linear predictive regression models can beat the historical mean model without any restrictions. Campbell and Thompson (2008) show the similar results when imposing some restrictions on the predictors. Yet our out-of-sample forecasting results show that linear predictive model has higher RMSE than historical mean model, and apparently it is consistent with Goyal and Welch (2008). Our nonparametric test is simplified as signal-to-noise ratio and it detects the nonlinear predictive component of the equity returns which contains more information the historical mean model can not provide. In this sense, we conclude that linear predictive regression models can beat the historical mean model. Following the same logic, our nonparametric predictive model can directly capture both the linear and nonlinear predictive components of the equity returns and it has a better out-of-sample forecasting performance. It is consistent with our nonparametric results in the previous sections.

Compared the individual forecast with the combined forecast, we find that combined predictive models have lower RMSE than individual predictive models for the same forecasting horizon h. Fama and French (1989) and others show that the existing predictor variables can detect changes in economic conditions that potentially signal fluctuations in the equity risk premium. But the dividend yield or term spread alone could capture different components of business conditions, and a given individual economic variable may give a number of "false signals" and/or imply an implausible equity risk premium during certain periods. Rapach, Strauss, and Zhou (2009) argue that if individual forecasts based on the predictors are weakly correlated, forecast combinatio should be less volatile and more reliably track movements in the equity risk premium. This is one explanation why the combined forecast methods outperform the individual forecast methods.

On the other hand, the nonparametric predictive model can fit the equity return better based on the predictors. First, nonparametric prediction generates a forecast with a variance near that of the smooth real equity return data, thereby reducing the noise in the individual predictive regression model forecasts. Second, combining forecast incorporates information from a host of economic variables while the historical average ignores economic variables. Combined forecasts have a substantially smaller bias than the historical average. Combining individual forecasts helps to reduce forecast variability.

2.6 CONCLUSION

The predictability of equity returns has been a long-standing problem in finance over decades. In this paper, we undertake an analysis of both in-sample and out-of-sample tests of stock return predictability in an effort to better understand the empirical evidence on return predictability. We use develop a reliable and powerful nonparametric predictability test and use it to examine whether there exists the predictability of equity returns for short and long horizons. We find that the prevailing variables, such as log dividend yields, log earnings yields, dividend payout ratio, short rate, inflation, book-to-market ratio, investment to capital ratio, corporate issuing activity, and consumption, wealth, and income ratio, have predictability power for equity returns at both short and long horizons. In contrast, the popular linear regression models cannot fully capture such predictability, apparently to due the neglected nonlinear predictable components. We also compare the conventional predictive regression models on predictor variables with the historical mean model according to Goyal and Welch (2007). We find that the prevailing predictive model outperforms the historical mean model in an out-of-sample content because it yields a smaller neglected signal-to-noise ratio.

We find that the poor out-of-sample performance of most linear prediction models is due to the limitation of linear models. We propose a nonparametric estimator to forecast the equity returns. Our nonparametric predictive models have lower RMSE than the historical mean model at both short-horizon and long-horizon. Our nonparametric prediction can improve the out-of-sample performance without restrictions. Using our nonparametric methods, both combined and individual forecast outperform the historical average. The combined forecast methods outperform the individual forecast methods.

APPENDIX

Proof of Theorem 1:

To prove theorem 1(i), we impose the following assumptions.

Assumption A.1: $\{Y_{t+h}, X_t\}$ is a stationary time series process with mixing condition. The marginal density function $g(x)$ of X_t is twice continuous differentiable with bounded second derivatives and $g(x)$ is strictly positive over the support of weighting function $w(\cdot)$ given in Assumption A.5. The dimension of X_t is d.

Assumption A.2: ε_{t+h} is a h-dependent process and ε_{t+h} is independent of $X_s, s \leq t.(a)$ $0 < E(\varepsilon_{t+h}^2|X_t) = \sigma_\varepsilon^2\ a.s.$; $(b) 0 < E(\varepsilon_{t+h}^4) = D$

Assumption A.3: $\sqrt{R}(\hat{\beta} - \beta) = O_P(1)$, where $\beta = p\lim \hat{\beta}$.

Assumption A.4: The kernel function $k : \mathbb{R} \to [0, 1]$ is a symmetic, and twice continuously differentiable probability density with bounded second derivatives.

Assumption A.5: $w(\cdot)$ is a positive continuous function over its support with $\int w(x)dx < \infty$ and $\int w^2(x)dx < \infty$.

Assumption A.6: $(i) b = b(n) = n^{-\alpha} \to \infty$,where $\alpha \in (0, 1/d)$ and $n = T - R$. $(ii) n^\lambda/R \to 0$, where $\lambda < \max\{1 - \alpha d, \frac{1}{2}(1 + \alpha d)\}$.

Assumption A.1 and A.2 are regularity conditions on the data generating process (DGP). Given $E(Y_{t+h}^2) < \infty$, there exists a measurable function $r_h(x) = E(\varepsilon_{t+h}|X_t = x)$ which is twice continuously differentiable with bounded second derivatives. Assumption A.3 allows for any in-sample $\sqrt{R}$-consistent estimator for β, which need not be asymptotically most efficient. Assumption A.4 is a standard regularity condition on kernel function $k(\cdot)$. Assumption A.5 is the regularity condition on the positive weighting function $w(\cdot)$. Assumption A.6 provides conditions on the bandwidth b and the relative speed between R and n, the sizes of the estimation sample and the prediction sample, respectively. Moreover, we allow the size of the prediction sample, n, to be larger or smaller than or the same as the size of the estimation sample, R. This offers a wide scope of applicability of our procedure, particularly when the whole sample $\{Y_t\}_{t=1}^T$ is relatively small.

Under the above regularity conditions, we have the following asymptotic results for the $\hat{\mathbf{Q}}_h$ statistics.

To measure the departure of $\hat{r}_h(x)$ from zero over all x, we use the following global measure

$\hat{Q}(h) = \frac{1}{n-h} \sum_{t=R+1}^{T-h} \widehat{r}_h^2(X_t) w(X_t)$. Define $\hat{Q}^*(h) = \int \widehat{r}_h^2(x) g(x) w(x) dx$.

Lemma 1.1: *Under the conditions of Theorem 1,* $(n-h)\hat{Q}(h) - (n-h)\hat{Q}^*(h) = o_p(b^{-d/2})$ *under* $\mathbb{H}_0$.

Proof of Lemma 1.1: Because $\hat{G}(x) - G(x) = O_p(n^{-1/2} (\ln n)^2)$ where $\hat{G}(x)$ is the empirical distribution function of X_t, and $(n-h) \int \widehat{r}_h^2(x) w(x) g(x) dx = O_p(b^{-d})$. Here we have made use of the well-known fact that

$$\sup_{x \in \mathbb{G}} \left| \hat{G}(x) - G(x) \right| = O_p(n^{-1/2} (\ln n)^2)$$

(see, e.g., Bentkus, Gotse and Tikhomirov (1997)) under Assumption A.1 and $\int \widehat{r}_h^2(x) w(x) g(x) dx = O_p(n^{-1} b^{-d})$ by Markov's inequality. We have

$$\begin{aligned}
(n-h)\hat{Q}(h) &= \sum_{t=R+1}^{T-h} \widehat{r}_h^2(X_t) w(X_t) \\
&= (n-h) \int \widehat{r}_h^2(x) w(x) dG(x) + (n-h) \int \widehat{r}_h^2(x) w(x) d[\hat{G}(x) - G(x)] \\
&= (n-h) \int \widehat{r}_h^2(x) g(x) w(x) dx + O_p(\sup_{x \in \mathbb{G}} |\hat{G}(x) - G(x)|) \\
& \quad (n-h) \int \widehat{r}_h^2(x) w(x) dG(x) \\
&= (n-h) \int \widehat{r}_h^2(x) g(x) w(x) dx + O_p(n^{-1/2} (\ln n)^2) O_p(b^{-d}) \\
&= (n-h) \int \widehat{r}_h^2(x) g(x) w(x) dx + o_p(b^{-d/2})
\end{aligned}$$

given $b \propto n^{-\alpha}$ for $\alpha \in (0, 1/d)$.This completes the proof. ■

Lemma 1.2: *Under the conditions of Theorem 1,* $(n-h)\hat{Q}^*(h) - (n-h)\widetilde{Q}(h) = (n-h) \int \widehat{r}_h^2(x) g(x) w(x) dx - (n-h) \int \widetilde{r}_h^2(x) g(x) w(x) dx = o_p(b^{-d/2})$,*under* $\mathbb{H}_0$.

Proof of Lemma 1.2: We decompose

$$\begin{aligned}
& (n-h) \int \widehat{r}_h^2(x) w(x) dG(x) - (n-h) \int \widetilde{r}_h^2(x) w(x) dG(x) \qquad \text{(A.1)} \\
=\ & (n-h) \int [\widehat{r}_h^2(x) - \widetilde{r}_h^2(x)] w(x) dG(x) \\
=\ & (n-h) \int [\widehat{r}_h(x) - \widetilde{r}_h(x)]^2 w(x) dG(x) + \\
& 2(n-h) \int \widetilde{r}_h(x) [\widehat{r}_h(x) - \widetilde{r}_h(x)] w(x) dG(x) \\
=\ & \hat{J}_1 + 2\hat{J}_2, \text{ say.}
\end{aligned}$$

For $\hat{J}_1$, we further decompose

$$\begin{aligned}
\hat{J}_1 &= (n-h)\int\left[\frac{(n-h)^{-1}\sum_{s=R+1}^{T-h}(\hat{\varepsilon}_{s+h}-\varepsilon_{s+h})\mathbf{K}_b(x-X_s)}{(n-h)^{-1}\sum_{s=R+1}^{T-h}\mathbf{K}_b(x-X_s)}\right]^2 dG(x) \qquad \text{(A.2)}\\
&= (n-h)\int\left[\frac{(n-h)^{-1}\sum_{s=R+1}^{T-h}(\hat{\varepsilon}_{s+h}-\varepsilon_{s+h})\mathbf{K}_b(x-X_s)}{\hat{g}(x)}\right]^2 dG(x)\\
&= (n-h)\int\frac{\left[(n-h)^{-1}\sum_{s=R+1}^{T-h}(\hat{\varepsilon}_{s+h}-\varepsilon_{s+h})\mathbf{K}_b(x-X_s)\right]^2}{g(x)}dx\\
&\quad +(n-h)\int\left[(n-h)^{-1}\sum_{s=R+1}^{T-h}(\hat{\varepsilon}_{s+h}-\varepsilon_{s+h})\mathbf{K}_b(x-X_s)\right]^2\\
&\quad \left[\frac{1}{\hat{g}^2(x)}-\frac{1}{g^2(x)}\right]g(x)dx\\
&= \hat{J}_{11}+\hat{J}_{12},\ \text{say.}
\end{aligned}$$

It suffices to consider the first term $\hat{J}_{11}$ in (A.2), since the second term $\hat{J}_{12}$ is a smaller order given $\sup_{x\in\mathbb{G}}|\hat{g}(x)-g(x)| \xrightarrow{p} 0$.Under the null hypothesis $E(\varepsilon_{t+h}|X_t)=0$, we define $E(\varepsilon_{t+h}|X_t)=a_n\delta(X_t)$ when $a_n\to 0$. Noting that $\hat{\varepsilon}_{s+h}-\varepsilon_{s+h}=\hat{\varepsilon}_{s+h}-\varepsilon_{ns+h}+\varepsilon_{ns+h}-\varepsilon_{s+h}$, we have

$$\begin{aligned}
\hat{J}_{11} &= (n-h)\int\frac{\left[(n-h)^{-1}\sum_{s=R+1}^{T-h}(\hat{\varepsilon}_{s+h}-\varepsilon_{ns+h})^2\mathbf{K}_b^2(x-X_s)\right]}{g(x)}dx \qquad \text{(A.3)}\\
&\quad +(n-h)\int\frac{\left[(n-h)^{-1}\sum_{s=R+1}^{T-h}(\varepsilon_{ns+h}-\varepsilon_{s+h})^2\mathbf{K}_b^2(x-X_s)\right]}{g(x)}dx\\
&\quad +2(n-h)\int\frac{\left[(n-h)^{-1}\sum_{s=R+1}^{T-h}(\hat{\varepsilon}_{s+h}-\varepsilon_{ns+h})(\varepsilon_{ns+h}-\varepsilon_{s+h})\mathbf{K}_b^2(x-X_s)\right]}{g(x)}dx\\
&= \hat{J}_{111}+\hat{J}_{112}+2\hat{J}_{113},
\end{aligned}$$

where

$$\begin{aligned}
\hat{J}_{111} &= (n-h)\int\frac{\left[(n-h)^{-1}\sum_{s=R+1}^{T-h}(\hat{\varepsilon}_{s+h}-\varepsilon_{ns+h})^2\mathbf{K}_b^2(x-X_s)\right]}{g(x)}dx \qquad \text{(A.4)}\\
&\le ||\widehat{\beta}-\beta||^2(n-h)\int\frac{\left[(n-h)^{-1}\sum_{s=R+1}^{T-h}||\nabla_\beta r_h(X_{s+h},\overline{\beta})||^2\mathbf{K}_b(x-X_s)\right]^2}{g(x)}dx\\
&= ||\widehat{\beta}-\beta||^2(n-h)=O_p(R^{-1/2})^2n=O_p(n/R)
\end{aligned}$$

by the mean-value theorem,

$$\begin{aligned}
\hat{J}_{112} &= (n-h)\int\frac{\left[(n-h)^{-1}\sum_{s=R+1}^{T-h}(\varepsilon_{ns+h}-\varepsilon_{s+h})^2\mathbf{K}_b^2(x-X_s)\right]^2}{g(x)}dx \qquad \text{(A.5)}\\
&= 0
\end{aligned}$$

and

$$\hat{J}_{113} = (n-h)\int \frac{\left[(n-h)^{-1}\sum_{s=R+1}^{T-h}(\hat{\varepsilon}_{s+h}-\varepsilon_{ns+h})(\varepsilon_{ns+h}-\varepsilon_{s+h})\mathbf{K}_b^2(x-X_s)\right]}{g(x)}dx \quad (A.6)$$
$$= 0$$

by the mean-value theorem. It follows from (A.1)–(A.6) that

$$\hat{J}_1 = O_p(n/R) \quad (A.7)$$

Next, we consider $\hat{J}_2$ in (A.1). Recalling that $\widetilde{r}_h^*(x)$ is defined in the same way as $\widetilde{r}_h(x)$ with ε_{ns+h} replacing ε_{s+h}, we decompose

$$\begin{aligned}\hat{J}_2 &= (n-h)\int \widetilde{r}_h(x)\left[\widehat{r}_h(x)-\widetilde{r}_h(x)\right]w(x)dG(x) \quad (A.8)\\ &= (n-h)\int \widetilde{r}_h(x)\left[\widehat{r}_h(x)-\widetilde{r}_h^*(x)\right]w(x)dG(x)+\\ &\quad (n-h)\int \widetilde{r}_h(x)\left[\widetilde{r}_h^*(x)-\widetilde{r}_h(x)\right]w(x)dG(x)\\ &= \hat{J}_{21}+\hat{J}_{22},\ \text{say.}\end{aligned}$$

For $\hat{J}_{21}$ in (A.8), by the second order Taylor series expansion, we have

$$\begin{aligned}\hat{J}_{21} &= (n-h)\int \widetilde{r}_h(x)\frac{(n-h)^{-1}\sum_{s=R+1}^{T-h}(\hat{\varepsilon}_{s+h}-\varepsilon_{ns+h})\mathbf{K}_b(x-X_s)}{\hat{g}(x)}w(x)dG(x) \quad (A.9)\\ &= (\widehat{\beta}-\beta)'(n-h)\int \widetilde{r}_h(x)\frac{(n-h)^{-1}\sum_{s=R+1}^{T-h}\nabla_\beta r_h(X_{s+h},\beta)\mathbf{K}_b(x-X_s)}{\hat{g}(x)}\\ &\quad w(x)dG(x)\\ &\quad +\frac{1}{2}(\widehat{\beta}-\beta)'(n-h)\int \widetilde{r}_h(x)\frac{(n-h)^{-1}\sum_{s=R+1}^{T-h}\nabla_\beta^2 r_h(X_{s+h},\overline{\beta})\mathbf{K}_b(x-X_s)}{\hat{g}(x)}\\ &\quad w(x)dG(x)(\widehat{\beta}-\beta)\\ &= O_p(R^{-1/2})nO_p(n^{-1/2})+O_p(R^{-1})nO_p(n^{-1/2}b^{-d})\\ &= O_p(R^{-1/2}n^{1/2})+O_p(R^{-1}n^{1/2}b^{-d}),\end{aligned}$$

by Hajék's projection, the Cauchy-Schwarz inequality, and $b \propto n^{-\alpha}$ for $\alpha \in (0,1/d)$. For $\hat{J}_{22}$ in (A.8), we have

$$\hat{J}_{22} = (n-h)a_n\int \widetilde{r}_h(x)\frac{(n-h)^{-1}\sum_{s=R+1}^{T-h}\delta(X_s)\mathbf{K}_b(x-X_s)}{\hat{g}(x)}dG(x) = 0 \quad (A.10)$$

It follows from (A.8)–(A.10) that $\hat{J}_2 = o_p(b^{-d/2})$. This, together with (A.1) and (A.7), yields the desired result. The proof of Lemma 1.2 is completed. ■

Lemma 1.3: *Under the conditions of Theorem 1,* $(n-h)\hat{Q}(h)-(n-h)\widetilde{Q}(h) = o_p(b^{-d/2})$ *under* $\mathbb{H}_0$.

Proof of Lemma 1.1: By Lemma 1.1 and Lemma 1.2, we have $(n-h)\hat{Q}(h)-(n-h)\widetilde{Q}(h) = o_p(b^{-d/2})$. ■

Lemma 1.4: *Under the conditions of Theorem 1,* $\widehat{\sigma}_\epsilon^2 = \sigma_\epsilon^2 + O_p(n^{-1/2})$ *under* $\mathbb{H}_0$.

Proof of Lemma 1.4: Since we know $\hat{\sigma}_\varepsilon^2 = (n-h)^{-1}\sum_{t=R+1}^{T-h}\hat{e}_{t+h}^2$, and $\hat{e}_{t+h} = \hat{\varepsilon}_{t+h} - \hat{r}_h(X_t)$, and the same definition for $\widetilde{\sigma}_\epsilon^2 = (n-h)^{-1}\sum_{t=R+1}^{T-h}\tilde{e}_{t+h}^2$ and $\tilde{e}_{t+h} = \varepsilon_{t+h} - \tilde{r}_h(X_t)$. Put $\hat{A}_t = \hat{\varepsilon}_{t+h} - \varepsilon_{t+h}$ and $\hat{B}_t = \hat{r}_h(X_t) - \tilde{r}_h(X_t)$, where $\tilde{r}_h(X_t)$ is defined in the same way as $\hat{r}_h(X_t)$ with ε_{t+h} replacing $\hat{\varepsilon}_{t+h}$. Then we have

$$\begin{aligned}
\hat{\sigma}_\epsilon^2 &= (n-h)^{-1}\sum_{t=R+1}^{T-h}\left[\hat{\varepsilon}_{t+h} - \hat{r}_h(X_t)\right]^2 \\
&= (n-h)^{-1}\sum_{t=R+1}^{T-h}\left\{(\hat{\varepsilon}_{t+h} - \varepsilon_{t+h}) - [\hat{r}_h(X_t) - \tilde{r}_h(X_t)] + [\varepsilon_{t+h} - \tilde{r}_h(X_t)]\right\}^2
\end{aligned}$$

and we can write

$$\hat{\sigma}_\epsilon^2 = \tilde{\sigma}_\epsilon^2 + (n-h)^{-1}\sum_{t=R+1}^{T-h}(\hat{A}_t - \hat{B}_t)^2 + 2(n-h)^{-1}\sum_{t=R+1}^{T-h}[\varepsilon_{t+h} - \tilde{r}_h(X_t)](\hat{A}_t - \hat{B}_t), \tag{A.11}$$

For the second term in (A.11), we first put

$$m_{st} = \frac{\mathbf{K}_b(x - X_s)}{\sum_{s=R+1}^{T-h}\mathbf{K}_h(x - X_s)}.$$

Then $\sum_{s=R+1}^{T-h} m_{st} = 1$ for all s and $\hat{B}_t = \sum_{s=R+1}^{T-h} m_{st}\hat{A}_s$. Under $\mathbb{H}_0$, we have

$$\begin{aligned}
\hat{A}_t &= Y_{t+h} - \hat{r}_h(X_t) - \varepsilon_{t+h} \qquad (A.12)\\
&= r_h(X_t,\beta) - \hat{r}_h(X_t,\hat{\beta}) + a_n\delta(X_t).
\end{aligned}$$

It follows that

$$\begin{aligned}
(n-h)^{-1}\sum_{t=R+1}^{T-h}(\hat{A}_t - \hat{B}_t)^2 &= (n-h)^{-1}\sum_{t=R+1}^{T-h}\left(\hat{A}_t - \sum_{s=1}^{n} m_{st}\hat{A}_s\right)^2 \qquad (A.13)\\
&\leq 4(n-h)^{-1}\sum_{t=R+1}^{T-h}\hat{A}_t^2 \\
&\leq 4(n-h)^{-1}\sum_{t=1}^{n}\left[r_h(X_t,\beta) - \hat{r}_h(X_t,\hat{\beta}) + a_n\delta(X_t)\right]^2 \\
&\leq 8(n-h)^{-1}\sum_{t=1}^{n}\left[r_h(X_t,\beta) - \hat{r}_h(X_t,\hat{\beta})\right]^2 \\
&= O_p(R^{-1})
\end{aligned}$$

where the first term is $O_p(R^{-1})$ by the mean-value theorem, and Assumptions A.2 and A.3.

For the third term in (A.11), we have

$$\begin{aligned} & (n-h)^{-1}\sum_{t=R+1}^{T-h}[\varepsilon_{t+h}-\tilde{r}_h(X_t)](\hat{A}_t-\hat{B}_t) \qquad \text{(A.14)} \\ = \ & (n-h)^{-1}\sum_{t=R+1}^{T-h}\varepsilon_{t+h}(\hat{A}_t-\hat{B}_t)-(n-h)^{-1}\sum_{t=R+1}^{T-h}\tilde{r}_h(X_t)(\hat{A}_t-\hat{B}_t) \\ = \ & \hat{T}_1-\hat{T}_2. \end{aligned}$$

For the $\hat{T}_2$ term, by the Cauchy-Schwarz inequality, we have

$$\begin{aligned} |\hat{T}_2| &\le \left[(n-h)^{-1}\sum_{t=R+1}^{T-h}\tilde{r}_h^2(X_t)\right]^{\frac{1}{2}}\left[(n-h)^{-1}\sum_{t=R+1}^{T-h}(\hat{A}_t-\hat{B}_t)^2\right]^{\frac{1}{2}} \qquad \text{(A.15)} \\ &= O_p(n^{-1/2}b^{-d/2})O_p(R^{-1/2}) = O_p(n^{-1/2}b^{-d/2}R^{-1/2}) \\ &= o_p(n^{-1/2}), \end{aligned}$$

given $Rb^d\to\infty$ and (A.13), where $(n-h)^{-1}\sum_{t=R+1}^{T-h}\tilde{r}_h^2(X_t)=O_p(n^{-1}b^{-d})$ by Markov's inequality, $E(\varepsilon_{t+h}|X_t)=0$ *a.s.* and Assumption A.1.

For the $\hat{T}_1$ term, we decompose

$$\begin{aligned} \hat{T}_1 &= (n-h)^{-1}\sum_{t=R+1}^{T-h}\varepsilon_{t+h}(\hat{A}_t-\hat{B}_t) \qquad \text{(A.16)} \\ &= (n-h)^{-1}\sum_{t=R+1}^{T-h}\varepsilon_{t+h}\hat{A}_t-(n-h)^{-1}\sum_{t=R+1}^{T-h}\varepsilon_{t+h}\hat{B}_t \\ &= \hat{T}_{11}-\hat{T}_{12}, \text{ say.} \end{aligned}$$

Here, using (A.12), we have

$$\begin{aligned} \hat{T}_{11} &= (n-h)^{-1}\sum_{t=R+1}^{T-h}\varepsilon_{t+h}\left[r_h(X_t,\beta)-\hat{r}_h(X_t,\hat{\beta})\right]+ \qquad \text{(A.17)} \\ & \quad a_n(n-h)^{-1}\sum_{t=R+1}^{T-h}\varepsilon_{t+h}\delta(X_t) \\ &= (n-h)^{-1}\sum_{t=R+1}^{T-h}\varepsilon_{t+h}\nabla_\beta r_h(X_{s+h},\beta)(\hat{\beta}-\beta) \\ & \quad +\frac{1}{2}(\widehat{\beta}-\beta)'(n-h)^{-1}\sum_{t=R+1}^{T-h}\varepsilon_{t+h}\nabla_\beta^2 r_h(X_{s+h},\beta)(\hat{\beta}-\beta) \\ &= O_p(n^{-1/2}R^{-1/2})+O_p(R^{-1}) \end{aligned}$$

where the first term is $O_p(n^{-1/2}R^{-1/2})$ by a second order Taylor series expansion, Chebyshev's inequality, the Cauchy-Schwarz inequality, and Assumptions A.2 and A.3; the second term is 0.

For the $\hat{T}_{12}$ term in (A.16), recalling $\hat{B}_t = \sum_{s=R+1}^{T-h} m_{st}\hat{A}_s$ and using (A.2), we have

$$\begin{aligned}
\hat{T}_{12} &= (n-h)^{-1}\sum_{t=R+1}^{T-h}\varepsilon_{t+h}\left[(n-h)^{-1}\sum_{s=R+1}^{T-h} m_{st}\hat{A}_s\right] \qquad\qquad (A.18)\\
&= (n-h)^{-1}\sum_{t=R+1}^{T-h}\varepsilon_{t+h}\left\{(n-h)^{-1}\sum_{s=R+1}^{T-h} m_{st}\left[r_h(X_t,\beta)-\hat{r}_h(X_t,\hat{\beta})\right]\right\}\\
&\quad +a_n(n-h)^{-1}\sum_{s=R+1}^{T-h}\varepsilon_{t+h}\sum_{s=R+1}^{T-h} m_{st}\delta(X_s)\\
&= O_p(n^{-1/2}R^{-1/2})+O_p(R^{-1})\\
&= o_p(n^{-1/2}),
\end{aligned}$$

where the order of each term follows by a similar reasoning to that for the $\hat{T}_{11}$ term.

Finally, for the first term $\tilde{\sigma}_\epsilon^2$ in (A.11), we have

$$\begin{aligned}
\tilde{\sigma}_\epsilon^2 &= (n-h)^{-1}\sum_{t=R+1}^{T-h}\varepsilon_{t+h}^2-(n-h)^{-1}2\sum_{t=R+1}^{T-h}\varepsilon_{t+h}\tilde{r}_h(X_t)+(n-h)^{-1}\sum_{t=R+1}^{T-h}\tilde{r}_h^2(X_t)\\
&= [\sigma_\epsilon^2+O_p(n^{-1/2})]+O_p(n^{-1}b^{-d/2})+O_p(n^{-1}b^{-d})\\
&= \sigma_\epsilon^2+O_p(n^{-1/2}),
\end{aligned}$$

given $\sum_{t=R+1}^{T-h}\tilde{r}_h^2(X_t)=O_p(n^{-1}b^{-d})$ by Markov's inequality and $\sum_{t=R+1}^{T-h}\varepsilon_{t+h}\tilde{r}_h(X_t)=O_p(n^{-1}b^{-d})$. Collecting (A.11) and (A.13)–(A.19) yields the desired result of this lemma. ■

Proof of Theorem 1:

The proof follows from theorem 3.4 (Hong and Lee (2009)) with suitable modifications with ϵ_t replaced by ϵ_{t+h}. ■

TABLES AND GRAPHICS

Table 2.1a. Bootstrap Results for Predictability Check

Panel a: DGP $A.0(h)$ follows $Y_{t+h}= \alpha_0+\varepsilon_{t+h}$. ε_{t+h} has a MA$(h-1)$ property. ρ is the autocoefficient of X_t and $\varepsilon_{t+h}=\sum_{j=1}^{h} \alpha_j v_{t+h-j}+v_{t+h}$.And $\{v_{t+h}\}$ and $\{u_t\}$ are mutually independent. The table presents the rejection rate of bootstrap results for different h, and autocoefficient ρ under three cases (1) p-Value < 0.10, (2) p-Value < 0.05, (3) p-Value < 0.01 via the number of iterations $T = 250, 500, 1000$.

DGP				p-Value 10%			p-Value 5%			p-Value 1%		
$A.0$	h	β	ρ	$T = 250$	500	1000	$T = 250$	500	1000	$T = 250$	500	1000
	1	0	0.1	0.077	0.110	0.114	0.040	0.065	0.062	0.012	0.018	0.015
			0.3	0.089	0.124	0.098	0.050	0.071	0.045	0.015	0.024	0.010
			0.5	0.084	0.110	0.102	0.040	0.066	0.047	0.010	0.025	0.011
			0.7	0.085	0.091	0.098	0.051	0.059	0.043	0.012	0.015	0.014
			0.9	0.091	0.097	0.100	0.058	0.052	0.062	0.011	0.018	0.019

Table 2.1b. Bootstrap Results for Predictability Check

Panel b: DGP $A.2(h)$ follows $Y_{t+h}= \beta_0+\beta_1 X_t^2+\varepsilon_{t+h}$. ε_{t+h} has a MA$(h-1)$ property. ρ is the autocoefficient of X_t. And $\varepsilon_{t+h}=\sum_{j=1}^{h} \alpha_j v_{t+h-j}+v_{t+h}$. And $\{v_{t+h}\}$ and $\{u_t\}$ are mutually independent. The table presents the rejection rate of bootstrap results for different h, and autocoefficient ρ under three cases (1) p-Value < 0.10, (2) p-Value < 0.05, (3) p-Value < 0.01 via the number of iterations $T = 250, 500, 1000$.

DGP				p-Value 10%			p-Value 5%			p-Value 1%		
$A.2$	h	β_1	ρ	$T = 250$	500	1000	$T = 250$	500	1000	$T = 250$	500	1000
	1	1	0.1	1.000	1.000	1.000	1.000	1.000	1.000	0.985	1.000	1.000
			0.3	1.000	1.000	1.000	1.000	1.000	1.000	0.989	1.000	1.000
			0.5	1.000	1.000	1.000	1.000	1.000	1.000	0.986	1.000	1.000
			0.7	1.000	1.000	1.000	1.000	1.000	1.000	0.989	1.000	1.000
			0.9	1.000	1.000	1.000	0.999	1.000	1.000	0.991	0.999	1.000

Table 2.1c. Bootstrap Results for Predictability Check

Panel c: DGP $A.1(h)$ follows $Y_{t+h} = \beta_0+\beta_1 X_t + \varepsilon_{t+h}$. ε_{t+h} has a MA$(h-1)$ property $\varepsilon_{t+h} = \sum_{j=1}^{h} \alpha_j v_{t+h-j} + v_{t+h}$. ρ is the autocoefficient of X_t. And $\{v_{t+h}\}$ and $\{u_t\}$ are mutually independent. The table presents the rejection rate of bootstrap results for different h, and autocoefficient ρ under three cases (1) p-Value < 0.10, (2) p-Value < 0.05, (3) p-Value < 0.01 via the number of iterations $T = 250, 500, 1000$.

(1) Test $H_0 : E(\varepsilon_{t+h}|X_t) = 0$, and $h = 1, 4, 12, 20$

DGP				p-Value 10%			p-Value 5%			p-Value 1%		
$A.1$	h	β	ρ	$T = 250$	500	1000	$T = 250$	500	1000	$T = 250$	500	1000
	1	0.5	0.1	0.091	0.108	0.097	0.051	0.060	0.055	0.014	0.015	0.011
			0.3	0.099	0.117	0.089	0.050	0.068	0.051	0.012	0.012	0.013
			0.5	0.101	0.110	0.100	0.046	0.064	0.058	0.014	0.013	0.011
			0.7	0.107	0.103	0.098	0.054	0.052	0.058	0.012	0.013	0.016
			0.9	0.111	0.107	0.086	0.069	0.059	0.046	0.019	0.015	0.016
	4	0.5	0.1	0.107	0.102	0.089	0.054	0.039	0.045	0.012	0.006	0.012
			0.3	0.093	0.092	0.095	0.054	0.052	0.050	0.015	0.015	0.008
			0.5	0.098	0.099	0.104	0.055	0.053	0.049	0.020	0.012	0.010
			0.7	0.097	0.113	0.100	0.051	0.065	0.061	0.012	0.023	0.014
			0.9	0.113	0.122	0.093	0.059	0.056	0.048	0.017	0.016	0.010
	12	0.5	0.1	0.081	0.090	0.091	0.045	0.052	0.052	0.012	0.009	0.013
			0.3	0.082	0.092	0.101	0.041	0.046	0.058	0.012	0.010	0.015
			0.5	0.091	0.085	0.103	0.042	0.046	0.061	0.011	0.014	0.013
			0.7	0.092	0.085	0.092	0.046	0.051	0.046	0.011	0.014	0.011
			0.9	0.088	0.108	0.088	0.040	0.062	0.049	0.009	0.017	0.014
	20	0.5	0.1	0.085	0.085	0.119	0.049	0.041	0.077	0.010	0.011	0.022
			0.5	0.082	0.092	0.097	0.041	0.052	0.049	0.009	0.017	0.013
			0.9	0.097	0.093	0.090	0.048	0.051	0.058	0.012	0.019	0.019

Table 2.1c. Bootstrap Results for Predictability Check

Panel c: DGP $A.1(h)$ follows $Y_{t+h} = \beta_0 + \beta_1 X_t + \varepsilon_{t+h}$. ε_{t+h} has a MA$(h-1)$ property $\varepsilon_{t+h} = \sum_{j=1}^{h} \alpha_j v_{t+h-j} + v_{t+h}$. ρ is the autocoefficient of X_t. And $\{v_{t+h}\}$ and $\{u_t\}$ are mutually independent. The table presents the rejection rate of bootstrap results for different h, and autocoefficient ρ under three cases (1) p-Value < 0.10, (2) p-Value < 0.05, (3) p-Value < 0.01 via the number of iterations $T = 250, 500, 1000$.

(2) Test $H_0 : E(Y_{t+h}|X_t) = E(Y_{t+h})$, and $h = 1, 4, 12, 20$

DGP				p-Value 10%			p-Value 5%			p-Value 1%		
$A.1$	h	β	ρ	$T=250$	500	1000	$T=250$	500	1000	$T=250$	500	1000
	1	0.1	0.1	0.107	0.183	0.310	0.062	0.121	0.218	0.010	0.034	0.083
		0.1	0.7	0.175	0.312	0.548	0.108	0.209	0.425	0.037	0.075	0.210
		0.3	0.1	0.649	0.955	0.998	0.526	0.910	0.997	0.249	0.729	0.981
		0.3	0.5	0.908	0.997	1.000	0.836	0.991	1.000	0.592	0.951	1.000
		0.5	0.5	0.993	1.000	1.000	0.984	1.000	1.000	0.913	0.999	1.000
		0.7	0.9	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
		0.9	0.7	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	4	0.1	0.1	0.104	0.175	0.282	0.054	0.099	0.193	0.007	0.028	0.060
		0.1	0.9	0.345	0.643	0.938	0.238	0.522	0.896	0.089	0.292	0.713
		0.3	0.1	0.620	0.917	0.999	0.498	0.869	0.997	0.217	0.642	0.974
		0.5	0.5	0.993	1.000	1.000	0.980	1.000	1.000	0.880	0.998	1.000
		0.7	0.9	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
		0.9	0.5	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	12	0.1	0.1	0.098	0.174	0.294	0.052	0.112	0.194	0.012	0.038	0.075
		0.1	0.9	0.336	0.623	0.938	0.234	0.502	0.889	0.079	0.273	0.717
		0.3	0.1	0.587	0.910	1.000	0.472	0.855	0.999	0.221	0.628	0.972
		0.5	0.5	0.987	1.000	1.000	0.971	1.000	1.000	0.863	1.000	1.000
		0.7	0.5	0.999	1.000	1.000	0.999	1.000	1.000	0.996	1.000	1.000
		0.9	0.5	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	20	0.1	0.1	0.094	0.167	0.303	0.056	0.074	0.217	0.020	0.020	0.077
		0.1	0.9	0.299	0.606	0.929	0.196	0.483	0.879	0.066	0.264	0.692
		0.3	0.1	0.559	0.889	0.998	0.424	0.808	0.994	0.194	0.572	0.961
		0.5	0.5	0.975	1.000	1.000	0.957	1.000	1.000	0.819	0.999	1.000
		0.7	0.5	1.000	1.000	1.000	1.000	1.000	1.000	0.984	1.000	1.000
		0.9	0.5	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000

Table 2.1d. Bootstrap Results for Predictability Check

Panel d: DGP $B.1(h)$ follows $Y_{t+h} = \beta_0 + \beta_1 X_t + \beta_2 X_t^2 + \varepsilon_{t+h}$. ε_{t+h} has a MA$(h-1)$ property $\varepsilon_{t+h} = \sum_{j=1}^{h} \alpha_j v_{t+h-j} + v_{t+h}$. ρ is the autocoefficient of X_t. And $\{v_{t+h}\}$ and $\{u_t\}$ are mutually independent. The table presents the rejection rate of bootstrap results for different h, and autocoefficient ρ under three cases (1) p-Value < 0.10, (2) p-Value < 0.05, (3) p-Value < 0.01 via the number of iterations $T = 250, 500, 1000$.

(1) Test $H_0 : E(\varepsilon_{t+h}|X_t) = 0$, and $h = 1, 4, 12, 20$

DGP					p-Value 10%			p-Value 5%			p-Value 1%		
$B.1$	h	β_1	β_2	ρ	$T = 250$	500	1000	$T = 250$	500	1000	$T = 250$	500	1000
	1	0.5	0.1	0.1	0.168	0.265	0.377	0.088	0.169	0.261	0.032	0.048	0.099
		0.5	0.1	0.5	0.215	0.377	0.590	0.132	0.274	0.475	0.039	0.118	0.241
		0.5	0.3	0.1	0.698	0.963	0.999	0.578	0.911	0.995	0.310	0.734	0.974
		0.5	0.3	0.5	0.874	0.996	1.000	0.808	0.989	1.000	0.585	0.930	1.000
		0.5	0.5	0.5	0.995	1.000	1.000	0.984	1.000	1.000	0.925	1.000	1.000
		0.5	0.7	0.7	1.000	1.000	1.000	1.000	1.000	1.000	0.990	1.000	1.000
		0.5	0.9	0.7	1.000	1.000	1.000	1.000	1.000	1.000	0.993	1.000	1.000
	4	0.5	0.1	0.1	0.178	0.229	0.394	0.103	0.155	0.283	0.024	0.040	0.101
		0.5	0.1	0.7	0.360	0.655	0.911	0.262	0.544	0.856	0.113	0.310	0.628
		0.5	0.3	0.1	0.656	0.947	1.000	0.537	0.898	0.999	0.298	0.708	0.977
		0.5	0.3	0.5	0.877	0.993	1.000	0.797	0.988	1.000	0.551	0.922	0.999
		0.5	0.5	0.5	0.997	1.000	1.000	0.991	1.000	1.000	0.921	0.999	1.000
		0.5	0.7	0.7	1.000	1.000	1.000	0.999	1.000	1.000	0.986	1.000	1.000
		0.5	0.9	0.7	1.000	1.000	1.000	1.000	1.000	1.000	0.988	1.000	1.000
	12	0.5	0.1	0.1	0.134	0.245	0.349	0.075	0.138	0.233	0.017	0.037	0.097
		0.5	0.1	0.5	0.188	0.335	0.586	0.105	0.224	0.460	0.028	0.076	0.220
		0.5	0.3	0.1	0.640	0.935	1.000	0.489	0.888	0.997	0.231	0.677	0.979
		0.5	0.3	0.5	0.845	0.994	1.000	0.754	0.985	1.000	0.496	0.918	0.999
		0.5	0.5	0.5	0.994	1.000	1.000	0.981	1.000	1.000	0.889	0.999	1.000
		0.5	0.7	0.5	0.999	1.000	1.000	0.998	1.000	1.000	0.963	1.000	1.000
		0.5	0.9	0.5	1.000	1.000	1.000	0.999	1.000	1.000	0.977	1.000	1.000
	20	0.5	0.1	0.1	0.140	0.235	0.410	0.079	0.146	0.286	0.016	0.035	0.110
		0.5	0.1	0.5	0.187	0.338	0.604	0.109	0.230	0.484	0.029	0.080	0.253
		0.5	0.3	0.1	0.610	0.934	1.000	0.466	0.882	0.999	0.206	0.670	0.981
		0.5	0.3	0.5	0.829	0.994	1.000	0.739	0.987	1.000	0.460	0.920	1.000
		0.5	0.5	0.5	0.993	1.000	1.000	0.975	1.000	1.000	0.867	0.997	1.000
		0.5	0.7	0.5	0.999	1.000	1.000	0.997	1.000	1.000	0.955	0.999	1.000
		0.5	0.9	0.5	1.000	1.000	1.000	0.999	1.000	1.000	0.973	0.999	1.000

Table 2.1d. Bootstrap Results for Predictability Check

Panel d: DGP $B.1(h)$ follows $Y_{t+h} = \beta_0+\beta_1 X_t + \beta_2 X_t^2 + \varepsilon_{t+h}$. ε_{t+h} has a MA$(h-1)$ property $\varepsilon_{t+h} = \sum_{j=1}^{h} \alpha_j v_{t+h-j} + v_{t+h}$. ρ is the autocoefficient of X_t. And $\{v_{t+h}\}$ and $\{u_t\}$ are mutually independent. The table presents the rejection rate of bootstrap results for different h, and autocoefficient ρ under three cases (1) p-Value < 0.10, (2) p-Value < 0.05, (3) p-Value < 0.01 via the number of iterations $T = 250, 500, 1000$.

(2) Test $H_0 : E(Y_{t+h}|X_t) = E(Y_{t+h})$, and $h = 1, 4, 12, 20$

DGP					p-Value 10%			p-Value 5%			p-Value 1%		
$B.1$	h	β_1	β_2	ρ	$T = 250$	500	1000	$T = 250$	500	1000	$T = 250$	500	1000
	1	0.1	0.1	0.1	0.176	0.338	0.610	0.089	0.237	0.475	0.026	0.078	0.212
		0.1	0.5	0.1	0.975	1.000	1.000	0.936	0.999	0.999	0.759	0.990	0.994
		0.3	0.1	0.1	0.694	0.963	1.000	0.561	0.921	0.999	0.310	0.748	0.985
		0.3	0.5	0.1	0.995	1.000	1.000	0.978	1.000	1.000	0.868	0.997	1.000
		0.5	0.5	0.1	1.000	1.000	1.000	0.997	1.000	1.000	0.967	1.000	1.000
		0.7	0.7	0.1	1.000	1.000	1.000	1.000	1.000	1.000	0.992	1.000	1.000
		0.9	0.9	0.1	1.000	1.000	1.000	1.000	1.000	1.000	0.996	1.000	1.000
	4	0.5	0.1	0.1	0.978	1.000	1.000	0.947	1.000	1.000	0.804	0.995	1.000
		0.5	0.1	0.5	0.993	1.000	1.000	0.982	1.000	1.000	0.906	0.999	1.000
		0.5	0.3	0.1	0.995	1.000	1.000	0.981	1.000	1.000	0.900	1.000	1.000
		0.5	0.3	0.5	0.997	1.000	1.000	0.991	1.000	1.000	0.945	1.000	1.000
		0.5	0.7	0.5	1.000	1.000	1.000	1.000	1.000	1.000	0.983	1.000	1.000
		0.5	0.9	0.5	1.000	1.000	1.000	1.000	1.000	1.000	0.987	1.000	1.000
	12	0.5	0.1	0.1	0.970	1.000	1.000	0.944	1.000	1.000	0.765	0.994	1.000
		0.5	0.1	0.5	0.989	1.000	1.000	0.978	1.000	1.000	0.882	0.998	1.000
		0.5	0.3	0.1	0.987	1.000	1.000	0.973	1.000	1.000	0.865	0.997	1.000
		0.5	0.3	0.5	0.994	1.000	1.000	0.988	1.000	1.000	0.936	0.998	1.000
		0.5	0.5	0.5	0.999	1.000	1.000	0.996	1.000	1.000	0.964	1.000	1.000
		0.5	0.9	0.5	1.000	1.000	1.000	1.000	1.000	1.000	0.980	1.000	1.000
	20	0.5	0.1	0.1	0.956	1.000	1.000	0.909	1.000	1.000	0.713	0.990	1.000
		0.5	0.1	0.5	0.979	1.000	1.000	0.955	1.000	1.000	0.836	0.993	1.000
		0.5	0.3	0.1	0.978	1.000	1.000	0.953	1.000	1.000	0.813	0.997	1.000
		0.5	0.3	0.5	0.995	1.000	1.000	0.984	1.000	1.000	0.905	0.998	1.000
		0.5	0.5	0.5	0.997	1.000	1.000	0.994	1.000	1.000	0.951	0.999	1.000
		0.5	0.9	0.5	0.999	1.000	1.000	0.997	1.000	1.000	0.975	1.000	1.000

Table 2.2. Sample statistics

Panel (a) reports summary statistics of the data for S&P 500, all at a quarterly frequency. Panel (b) reports statistics for monthly frequency . Excess returns and short rates are continuously compounded. Sample means and standard deviations (SD) for excess returns, dividend, and earnings growth have been annualized by multiplying by 4(12) and $\sqrt{4}(\sqrt{12})$, respectively, for the case of quarterly (monthly) frequency data. Short rates are three-month T-bill rates. Dividend and earnings yields, and the corresponding dividend and earnings growth are computed using dividends or earnings summed up over the past year. Panel (c) reports statistics for annually frequency. The unit root test is the Phillips and Perron (1988) test for the estimated regression $x_t = \alpha + \rho x_{t-1} + u_t$ under the null $x_t = x_{t-1} + u_t$. The critical values corresponding to p-values of 0.01, 0.025, 0.05, and 0.10 are 3:46, 3:14, 2:88, and 2:57, respectively. $^{*}p < 0.05.^{**}p < 0.01$.

Panel (a) US S&P500 data, March 1936-December 2001 Quarterly

	Excess Return	Short Rate	Dividend Yield	earnings Yield	Dividend Growth	Earnings Growth
Mean	0.0803	0.0416	0.0408	0.0769	0.0566	0.0599
S.D.	0.3336	0.0320	0.0157	0.0299	0.1578	0.2303
Auto	0.092	0.9531	0.9221	0.9516	0.4306	0.6926
Test statistics						
H_0: unit root	-13.97^{*}	-2.9290	-4.0337	-1.5765	-9.72^{**}	-6.37^{**}

Panel (b) US S&P500 data, January 1970-December 2006 monthly

	Excess Return	Short Rate	Dividend Yield	earnings Yield
Mean	0.0610	0.0597	0.0317	0.0694
S.D.	0.5259	0.0288	0.0129	0.0299
Auto	0.081	0.992	0.978	0.987
Test statistics				
H_0: unit root	-28.34^{*}	-1.28	-1.51	-1.17

Panel (c) US S&P500 data, 1872-2005 annually

	Excess Return	Short Rate	Dividend Yield	earnings Yield	Dividend Payout Ratio	Inflation 1919−2005	b/m 1921−2005	i/k 1947−2005	ntis 1927−2005	eqis 1927−2005	cay 1945−2005
Mean	0.0171	0.0479	0.0451	0.0750	0.6213	0.0309	1.6924	0.0836	0.0229	0.1986	−0.0488
S.D.	0.170	0.0278	0.0163	0.0273	0.1987	0.0464	0.5338	0.0343	0.0772	0.1099	1.4925
Auto	0.077	0.831	0.762	0.737	0.615	0.566	0.918	0.912	0.436	0.493	0.564
Test statistics											
H_0: unit root	-10.53^{**}	-1.05	-1.53	-1.54	-1.67	-4.32^{**}	-0.90	-3.63^{**}	-7.82^{**}	-2.33^{*}	-4.30^{**}

Table 2.3a. Predictability of US Excess Returns(Quarterly)

We estimate regressions of the form $Y_{t+h} = \alpha_h + \beta_h' X_t + \varepsilon_{h,t+h}$ where $Y_{t+h} = (\tau/h)[(y_{t+1} - r_t) + \cdots + (y_{t+h} - r_{t+h-1})]$ is the annualized h-period excess return for the aggregate stock market, r_t is the risk-free rate from t to $t+1$, and $y_{t+1} - r_t$ is the excess one period return from time t to $t+1$, with instruments z_t being log dividend yields or log earnings yields. T-statistics in parentheses are computed using Newey West(1987) and Hodrick (1992) standard errors. Horizons h are quarterly. The test column reports a p-value for the predictictability test under two hypothesises $H2$ and $H2$. Hypothesis $H2$ is H_0: $E(Y_{t+h}|X_t) = E(Y_{t+h})$ and Hypothesis $H2$ is H_0: $E(\varepsilon_{t+h}|X_t) = 0$. $^*p < 0.05$.$^{**}p < 0.01$. The time periods are from 1936 to 2001, from 1952 to 2001, from 1936 to 1990, and from 1952 to 1990.

		Univariate Regression							
	k	$dy4$		Test		$ey4$		Test	
		(1)NW	(2)HK	(1)H1	(2)H2	(1)NW	(2)HK	(1)H1	(2)H2
1936 −2001	1	0.1441	0.1441	0.0565	0.0758	0.0630	0.0625	0.2526	0.0901
		(2.28)*	(1.824)	(0.000)**	(0.000)**	(0.91)	(0.70)	(0.000)**	(0.000)**
	4	0.1618	0.1578	0.0525	0.1649	0.0918	0.0898	0.0379	0.0677
		(2.81)**	(2.030)	(0.000)**	(0.000)**	(1.42)	(1.30)	(0.015)*	(0.000)**
	12	0.1522	0.1455	0.0390	0.0454	0.0648	0.549	0.0377	0.0537
		(2.92)**	(1.568)	(0.000)**	(0.000)**	(1.05)	(0..90)	(0.016)*	(0.000)**
	20	0.1846	0.1028	0.0921	0.1552	0.0484	0.0348	0.0490	0.0549
		(3.84)**	(1.364)	(0.000)**	(0.000)**	(0.81)	(0.54)	(0.000)**	(0.000)**
1952 −2001	1	0.0417	0.0489	0.1048	0.1129	0.0467	0.0464	0.2952	0.0984
		(0.51)	(0.771)	(0.000)**	(0.000)**	(0.59)	(0.46)	(0.000)**	(0.000)**
	4	0.0542	0.0530	0.1558	0.0910	0.0791	0.0798	0.1260	0.1178
		(0.69)	(0.773)	(0.000)**	(0.000)**	(1.41)	(1.218)	(0.000)**	(0.000)**
	12	0.0091	0.0234	0.0244	0.0454	0.0768	0.0756	0.0683	0.0887
		(0.12)	(0.344)	(0.024)*	(0.000)**	(1.25)	(1.03)	(0.000)**	(0.000)**
	20	0.0276	0.0287	0.0921	0.1552	0.0283	0.0223	0.1005	0.1065
		(0.35)	(0.477)	(0.000)**	(0.000)**	(1.80)	(0.320)	(0.000)**	(0.000)**
1936 −1990	1	0.2993	0.2203	0.0315	0.0515	0.0886	0.0896	0.3864	0.0387
		(3.19)**	(2.416)*	(0.021)*	(0.000)**	(1.57)	(1.304)	(0.000)**	(0.015)*
	4	0.3228	0.2383	0.1560	0.0689	0.1417	0.1473	0.0333	0.0361
		(4.56)**	(3.097)**	(0.000)**	(0.000)**	(1.52)	(2.309)*	(0.019)*	(0.017)*
	12	0.2744	0.2380	0.1069	0.1016	0.0957	0.0945	0.0555	0.0979
		(5.08)**	(4.08)**	(0.000)**	(0.000)**	(1.29)	(1.02)	(0.000)**	(0.000)**
	20	0.2652	0.1787	0.1326	0.1042	0.1225	0.1078	0.0924	0.0882
		(5.97)**	(2.819)**	(0.000)**	(0.000)**	(1.38)	(1.392)	(0.000)**	(0.000)**
1952 −1990	1	0.1622	0.1482	0.0851	0.1006	0.1537	0.1028	0.2496	0.0223
		(1.06)	(2.783)**	(0.000)**	(0.000)**	(0.60)	(1.168)	(0.000)**	(0.022)*
	4	0.1921	0.3070	0.0682	0.0639	0.1291	0.1287	0.0809	0.0685
		(1.40)	(2.50)*	(0.000)**	(0.000)**	(1.62)	(1.521)	(0.000)**	(0.000)**
	12	0.0988	0.1132	0.1849	0.1318	0.0576	0.0475	0.0732	0.1356
		(0.80)	(1.453)	(0.000)**	(0.000)**	(0.75)	(0.45)	(0.000)**	(0.000)**
	20	0.0622	0.0845	0.2669	0.1138	0.0771	0.0798	0.3169	0.1878
		(0.67)	(1.916)	(0.000)**	(0.000)**	(1.17)	(1.133)	(0.000)**	(0.000)**

Table 2.3b. Predictability of US Excess Returns(Quarterly)

We estimate regressions of the form $Y_{t+h} = \alpha_h + \beta_h' X_t + \varepsilon_{h,t+h}$ where $Y_{t+h} = (\tau/h)[(y_{t+1} - r_t) + \cdots + (y_{t+h} - r_{t+h-1})]$ is the annualized h-period excess return for the aggregate stock market, r_t is the risk-free rate from t to $t+1$, and $y_{t+1} - r_t$ is the excess one period return from time t to $t+1$, with instruments z_t being log dividend yields and risk free rate together. T-statistics in parentheses are computed using Newey West(1987) and Hodrick (1992) standard errors. Horizons h are quarterly. The test column reports a p-value for the predictictability test under six hypothesises $H1-H6$. X_1 represents the short rate r and X_2 represents the dividend yields. Hypothesis $H1$ ($H_0 : E(Y_{t+h}|X_{1t}) = E(Y_{t+h})$), Hypothesis $H2$ ($H_0 : E(\varepsilon_{t+h}|X_{1t}) = 0$),Hypothesis $H3$ ($H_0 : E(Y_{t+h}|X_{1t}) = E(Y_{t+h})$), Hypothesis $H4$ ($H_0 : E(\varepsilon_{t+h}|X_{2t}) = 0$), Hypothesis $H5$ ($H_0 : E(Y_{t+h}|X_{1t}, X_{2t}) = E(Y_{t+h})$), Hypothesis $H6$ ($H_0 : E(\varepsilon_{t+h}|X_{1t}, X_{2t}) = 0$). $^{*}p < 0.05$. $^{**}p < 0.01$. The time periods are from 1936 to 2001, from 1952 to 2001, from 1936 to 1990, and from 1952 to 1990.

		BivariateRegression				Test					
	k	r		$dy4$							
		(1)NW	(2)HK	(1)NW	(2)HK	(1)H1	(2)H2	(3)H3	(4)H4	(5)H5	(6)H6
1936 −2001	1	−0.9864	−1.0888	0.0849	0.0875	0.0409	0.0495	0.0475	0.0699	0.0088	0.0137
		(−5.730)**	(−1.608)	(1.530)	(1.530)	(0.010)**	(0.008)**	(0.005)**	(0.000)**	(0.044)*	(0.032)*
	4	−0.8305	−0.5596	0.1068	0.1032	0.0694	0.0600	0.0525	0.0761	0.0064	0.0168
		(−5.520)**	(−0.827)	(2.200)*	(1.865)	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.052)	(0.028)*
	12	−0.6993	−0.4321	0.0985	0.0980	0.0533	0.0469	0.0701	0.0892	0.0059	0.0072
		(−8.57)**	(−0.708)	(2.530)*	(1.265)	(0.000)**	(0.006)**	(0.000)**	(0.000)**	(0.056)	(0.046)*
	20	−0.6606	−0.6364	0.1246	0.1152	0.0634	0.1278	0.0913	0.2218	0.0040	0.0043
		(−8.83)**	(1.196)	(3.57)**	(1.255)	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.062)	(0.064)
1952 −2001	1	−1.2958	−2.1623	0.1355	0.1362	0.1147	0.1236	(0.1593)	0.1151	0.0123	0.0095
		(−6.74)**	(−2.912)**	(1.91)*	(2.152)*	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.034)*	(0.040)*
	4	−1.0484	−1.4433	0.1291	0.1313	0.1548	0.1316	0.1558	0.0909	0.0338	0.0472
		(−5.85)**	(−1.930)	(1.990)*	(1.921)	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.017)*	(0.005)**
	12	−0.7141	−0.6272	0.0685	0.0874	0.0712	0.0488	0.0335	0.0823	0.0108	0.0153
		(−6.61)**	(−0.987)	(1.17)	(0.680)	(0.000)**	(0.006)**	(0.016)*	(0.000)**	(0.035)*	(0.031)*
	20	−0.5738	−0.4829	0.0596	0.0774	0.0534	0.0690	0.0759	0.1468	0.0198	0.0081
		(−5.99)**	(−0.745)	(1.00)	(0.600)	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.026)*	(0.048)*
1936 −1990	1	−0.9709	−1.0380	0.1961	0.1917	0.0325	0.0321	0.0510	0.0503	0.0091	0.0090
		(−5.49)**	(−1.543)	(2.44)*	(2.126)*	(0.021)*	(0.021)*	(0.000)**	(0.000)**	(0.044)*	(0.045)*
	4	−0.8131	−0.4865	0.2398	0.2254	0.0386	0.0390	0.0661	0.0698	0.0142	0.0144
		(−5.34)**	(−0.714)	(4.21)**	(3.006)**	(0.015)*	(0.012)*	(0.000)**	(0.000)**	(0.034)*	(0.032)*
	12	−0.7121	−0.6785	0.2114	0.1898	0.0827	0.0603	0.1069	0.0633	0.0126	0.0139
		(−8.26)**	(−0.879)	(5.65)**	(3.214)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.035)*	(0.033)*
	20	−0.6877	−0.6458	0.2097	0.1719	0.0791	0.0222	0.2107	0.0580	0.0335	0.0045
		(−8.58)**	(−1.289)	(7.43)**	(2.832)**	(0.000)**	(0.024)*	(0.000)**	(0.000)**	(0.017)*	(0.061)
1952 −1990	1	−1.4347	−2.7329	0.4102	0.4125	0.0947	0.1134	0.0851	0.0823	0.0183	0.0224
		(−6.29)**	(3.504)**	(3.02)**	(3.672)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.029)*	(0.022)*
	4	−1.1908	−1.9840	0.4030	0.3935	0.0892	0.1049	0.0683	0.0607	0.0273	0.0193
		(−6.26)**	(−2.508)*	(3.78)**	(3.700)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.019)*	(0.025)*
	12	−0.8431	−0.7324	0.2623	0.2457	0.1210	0.0716	0.1849	0.1381	0.0628	0.0361
		(−9.02)**	(−1.278)	(4.28)**	(2.457)*	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.018)*
	20	−0.6679	−0.7120	0.2024	0.2057	0.3003	0.0541	0.2679	0.1058	0.1149	0.0029
		(−7.47)**	(−1.087)	(4.09)**	(2.387)*	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.112)

Table 2.3c. Predictability of US Excess Returns(Quarterly)

We estimate regressions of the form $Y_{t+h} = \alpha_h + \beta_h' X_t + \varepsilon_{h,t+h}$ where $Y_{t+h} = (\tau/h)[(y_{t+1} - r_t) + \cdots + (\ y_{t+h} - r_{t+h-1})$ is the annualized h-period excess return for the aggregate stock market, r_t is the risk-free rate from t to $t+1$, and $y_{t+1} - r_t$ is the excess one period return from time t to $t+1$, with instruments z_t being log dividends yields and log earnings yields together. T-statistics in parentheses are computed using Newey West(1987) and Hodrick (1992) standard errors. Horizons h are quarterly. The test column reports a p-value for the predictictability test under six hypothesises $H1{-}H6$. X_1 represents the short rate r and X_2 represents the earnings yields. Hypothesis $H1$ $(H_0 : E(Y_{t+h}|X_{1t}) = E(Y_{t+h}))$, Hypothesis $H2$ $(H_0 : E(\varepsilon_{t+h}|X_{1t}) = 0)$,Hypothesis $H3$ $(H_0 : E(Y_{t+h}|X_{1t}) = E(Y_{t+h}))$, Hypothesis $H4$ $(H_0 : E(\varepsilon_{t+h}|X_{2t}) = 0)$, Hypothesis $H5$ $(H_0 : E(Y_{t+h}|X_{1t}, X_{2t}) = E(Y_{t+h}))$, Hypothesis $H6$ $(H_0 : E(\varepsilon_{t+h}|X_{1t}, X_{2t}) = 0)$. $^{*}p < 0.05.^{**}p < 0.01.$The time periods are from 1936 to 2001, from 1952 to 2001, from 1936 to 1990, and from 1952 to 1990.

		BivariateRegression				Test					
	k	$dy4$ (1)NW	(2)HK	$ey4$ (1)NW	(2)HK	(1)H1	(2)H2	(3)H3	(4)H4	(5)H5	(6)H6
1936 −2001	1	0.3891	0.1842	−0.3003	−0.1019	0.0475	0.0771	0.0781	0.0887	0.0303	0.0482
		$(3.08)^{**}$	(1.330)	$(-2.27)^{*}$	(−0.741)	$(0.008)^{**}$	$(0.000)^{**}$	$(0.000)^{**}$	$(0.000)^{**}$	$(0.018)^{*}$	$(0.006)^{**}$
	4	0.3485	0.1119	−0.2289	0.0012	0.0526	0.0781	0.0379	0.0680	0.0209	0.0211
		$(3.11)^{**}$	(0.981)	$(-1.97)^{*}$	(0.011)	$(0.000)^{**}$	$(0.000)^{**}$	$(0.015)^{*}$	$(0.000)^{**}$	$(0.025)^{*}$	$(0.024)^{*}$
	12	0.3503	0.1470	−0.2263	−0.1020	0.0701	0.0400	0.0306	0.0385	0.0148	0.0091
		$(3.36)^{**}$	(1.40)	$(-2.19)^{*}$	(−1.39)	$(0.000)^{**}$	$(0.011)^{*}$	$(0.018)^{*}$	$(0.014)^{*}$	$(0.030)^{*}$	$(0.044)^{*}$
	20	0.4752	0.2111	−0.3119	−0.0912	0.0913	0.0495	0.1493	0.1495	0.0121	0.0189
		$(5.05)^{**}$	(1.55)	$(-3.64)^{**}$	(−1.64)	$(0.000)^{**}$	$(0.000)^{**}$	$(0.000)^{**}$	$(0.000)^{**}$	$(0.035)^{*}$	$(0.027)^{*}$
1952 −2001	1	0.3857	0.1948	−0.3953	−0.1113	0.1593	0.0945	0.0941	0.0468	0.0898	0.0447
		$(2.46)^{*}$	(1.557)	$(-2.61)^{**}$	(−0.873)	$(0.000)^{**}$	$(0.000)^{**}$	$(0.000)^{**}$	$(0.009)^{**}$	$(0.000)^{**}$	$(0.010)^{**}$
	4	0.3584	0.1615	−0.3485	−0.0636	0.1139	0.1161	0.1682	0.1255	0.0865	0.0810
		$(2.57)^{*}$	(1.195)	$(-2.83)^{**}$	(−0.450)	$(0.000)^{**}$	$(0.000)^{**}$	$(0.000)^{**}$	$(0.000)^{**}$	$(0.000)^{**}$	$(0.000)^{**}$
	12	0.2843	0.1821	−0.2969	−0.0832	0.0336	0.0202	0.0458	0.0388	0.0087	0.0071
		(1.87)	(1.21)	$(-2.65)^{**}$	(−0.76)	$(0.016)^{*}$	$(0.026)^{*}$	$(0.009)^{**}$	$(0.014)^{*}$	$(0.045)^{*}$	$(0.046)^{*}$
	20	0.3567	0.1458	−0.3402	−0.0765	0.0821	0.0986	0.0851	0.1001	0.0266	0.0525
		$(2.23)^{*}$	(0.561)	$(-3.32)^{**}$	(−0.520)	$(0.000)^{**}$	$(0.000)^{**}$	$(0.000)^{**}$	$(0.000)^{**}$	$(0.022)^{*}$	$(0.000)^{**}$
1936 −1990	1	0.7476	0.3848	−0.4719	−0.1800	0.0510	0.0497	0.0351	0.0388	0.0192	0.0221
		$(4.23)^{**}$	(1.849)	$(-2.99)^{**}$	(1.062)	$(0.000)^{**}$	$(0.000)^{**}$	$(0.019)^{*}$	$(0.014)^{*}$	$(0.027)^{*}$	$(0.024)^{*}$
	4	0.6859	0.2869	−0.3823	−0.0532	0.0662	0.0666	0.0333	0.0381	0.0121	0.0163
		$(4.58)^{**}$	(1.872)	$(-2.76)^{**}$	(−0.411)	$(0.000)^{**}$	$(0.000)^{**}$	$(0.020)^{*}$	$(0.015)^{*}$	$(0.035)^{*}$	$(0.031)^{*}$
	12	0.6320	0.2987	−0.3677	−0.789	0.0706	0.0751	0.1741	0.1994	0.0501	0.0550
		$(5.26)^{**}$	(1.98)	$(-3.03)^{**}$	(−0.93)	$(0.000)^{**}$	$(0.000)^{**}$	$(0.000)^{**}$	$(0.000)^{**}$	$(0.000)^{**}$	$(0.000)^{**}$
	20	0.6521	0.1916	−0.4005	−0.0139	0.1486	0.1245	0.0901	0.0834	0.1018	0.0824
		$(6.77)^{**}$	(1.874)	$(-4.25)^{**}$	(−0.181)	$(0.000)^{**}$	$(0.000)^{**}$	$(0.000)^{**}$	$(0.000)^{**}$	$(0.000)^{**}$	$(0.000)^{**}$
1952 −1990	1	1.3055	0.9349	−0.94	−0.5240	0.0851	0.0907	0.0271	0.0219	0.0112	0.0089
		$(4.05)^{**}$	$(3.71)^{**}$	$(-3.90)^{**}$	$(-2.618)^{**}$	$(0.000)^{**}$	$(0.000)^{**}$	$(0.021)^{*}$	$(0.024)^{*}$	$(0.036)^{*}$	$(0.045)^{*}$
	4	1.2350	0.8210	−0.8581	−0.4212	0.0683	0.0592	0.0809	0.0564	0.0427	0.0329
		$(4.35)^{**}$	$(3.234)^{**}$	$(-4.21)^{**}$	$(-2.080)^{*}$	$(0.000)^{**}$	$(0.000)^{**}$	$(0.000)^{**}$	$(0.000)^{**}$	$(0.009)^{**}$	$(0.016)^{*}$
	12	1.0544	0.7824	−0.7689	−0.7320	0.0098	0.0648	0.0910	0.1074	0.0041	0.0311
		$(6.89)^{**}$	$(2.98)^{**}$	$(-6.38)^{**}$	$(-3.54)^{**}$	$(0.043)^{*}$	$(0.000)^{**}$	$(0.000)^{**}$	$(0.000)^{**}$	(0.061)	$(0.017)^{*}$
	20	0.8561	0.4167	−0.6423	−0.1999	(0.0212)	0.0511	0.0458	0.0875	0.0824	0.0551
		$(8.14)^{**}$	$(2.685)^{**}$	$(-7.43)^{**}$	(−1.570)	$(0.025)^{*}$	$(0.000)^{**}$	$(0.006)^{**}$	$(0.000)^{**}$	$(0.000)^{**}$	$(0.000)^{**}$

Table 2.3d. Predictability of US Excess Returns(Quarterly)

(a)We estimate regressions of the form $Y_{t+h} = \alpha_h + \beta_h' X_t + \varepsilon_{h,t+h}$ where $Y_{t+h} = (\tau/h)[(y_{t+1} - r_t) + \cdots + (\ y_{t+h} - r_{t+h-1})$ is the annualized h-period excess return for the aggregate stock market, r_t is the risk-free rate from t to $t+1$, and $y_{t+1} - r_t$ is the excess one period return from time t to $t+1$, with instruments z_t being short rate, log dividends yields, and log earnings yields together. T-statistics in parentheses are computed using Newey West(1987) and Hodrick (1992) standard errors. Horizons h are quarterly. The time periods are from 1936 to 2001, from 1952 to 2001, from 1936 to 1990, and from 1952 to 1990.

(b)The test column reports a p-value for the predictictability test under six hypothesises $H1 - H8$. X_1 represents the short rate r , X_2 represents the dividends yields and X_3 represents the earnings yields. Hypothesis $H1$ ($H_0 : E(Y_{t+h}|X_{1t}) = E(Y_{t+h})$), Hypothesis $H2$ ($H_0 : E(\varepsilon_{t+h}|X_{1t}) = 0$),Hypothesis $H3$ ($H_0 : E(Y_{t+h}|X_{1t}) = E(Y_{t+h})$), Hypothesis $H4$ ($H_0 : E(\varepsilon_{t+h}|X_{2t}) = 0$), Hypothesis $H5$ ($H_0 : E(Y_{t+h}|X_{3t}) = E(Y_{t+h})$), Hypothesis $H6$ ($H_0 : E(\varepsilon_{t+h}|X_{3t}) = 0$),Hypothesis $H7$ ($H_0 : E(Y_{t+h}|X_{1t}, X_{2t}, X_{3t}) = E(Y_{t+h})$), Hypothesis $H8$ ($H_0 : E(\varepsilon_{t+h}|X_{1t}, X_{2t}, X_{3t}) = 0$). $^*p < 0.05$.$^{**}p < 0.01$.

	k	TrivariateRegression r (1)NW	r (2)HK	$dy4$ (1)NW	$dy4$ (2)HK	$ey4$ (1)NW	$ey4$ (2)HK
1936 −2001	1	−1.0703	−1.0334	0.1018	0.1000	−0.0132	−0.0168
		(−5.40)**	(−1.296)	(0.80)	(0.605)	(−0.090)	(−0.103)
	4	−0.9325	−0.7759	0.0094	0.0472	0.1237	0.0654
		(−5.65)**	(−1.084)	(0.31)	(0.377)	(1.26)	(0.556)
	12	−0.7717	−0.6836	0.0175	0.0125	0.0862	0.0632
		(−8.49)**	(−1.923)	(0.20)	(0.042)	(1.10)	(0.70)
	20	−0.6231	−0.4190	0.1685	0.0666	−0.0435	0.0291
		(−6.63)**	(−0.682)	(1.79)	(0.486)	(−0.52)	(0.361)
1952 −2001	1	−1.4102	−2.6243	0.0327	0.0337	0.1276	0.1272
		(−6.04)**	(−2.85)**	(0.21)	(0.239)	(0.80)	(0.815)
	4	−1.1074	−1.8146	0.0755	0.0479	0.0662	0.0629
		(−5.01)**	(−2.063)*	(0.56)	(0.687)	(0.52)	(0.487)
	12	−0.6863	−1.0213	0.0988	0.0453	−0.0337	−0.0134
		(−5.43)**	(−2.34)*	(0.81)	(0.43)	(−0.31)	(−0.23)
	20	−0.4535	−0.3548	0.2209	0.1199	−0.1591	−0.0418
		(−3.62)**	(−0.489)	(1.54)	(0.432)	(−1.36)	(−0.249)
1936 −1990	1	−0.9918	−0.6544	0.3706	0.3051	0.0245	0.0125
		(−4.64)**	(−0.696)	(1.84)	(1.112)	(0.15)	(0.099)
	4	−0.852	−0.4708	0.1932	0.2300	0.0449	−0.0046
		(−4.98)**	(−0.031)	(1.33)	(1.336)	(0.38)	(−0.031)
	12	−0.6939	−0.4873	0.2341	0.2032	−0.0217	−0.0312
		(−8.11)**	(−6.46)**	(2.33)	(1.90)	(−0.24)	(−0.32)
	20	−0.6067	−0.4239	0.3085	0.1423	−0.0955	0.0297
		(−6.43)**	(−0.714)	(3.19)**	(1.597)	(−1.10)	(0.431)
1952 −1990	1	−1.2799	−2.0892	0.6690	0.6598	−0.2348	−0.2418
		(−5.13)**	(−2.096)*	(1.84)	(1.78)	(−0.87)	(−0.949)
	4	−0.9802	−1.3320	0.7451	0.6565	−0.3121	−0.2392
		(−4.72)**	(−1.376)	(2.65)**	(2.303)*	(−1.58)	(−0.960)
	12	−0.5595	−0.4578	0.7738	0.6719	−0.4558	−0.3722
		(−6.62)**	(−2.23)*	(6.71)**	(2.13)*	(−4.14)**	(−1.80)
	20	−0.4047	−0.3068	0.6553	0.3793	−0.4111	−0.1570
		(−3.27)**	(−0.374)	(5.24)**	(2.188)*	(−3.23)**	(−0.991)

	k	Trivariate Regression Test (1)H1	(2)H2	(3)H3	(4)H4	(5)H5	(6)H6	(7)H7	(8)H8
1936 −2001	1	0.0409	0.0509	0.0475	0.0600	0.0781	0.0888	0.0089	0.0157
		(0.013)*	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.044)*	(0.026)*
	4	0.0694	0.0645	0.0526	0.0781	0.0379	0.0676	0.0058	0.0166
		(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.015)*	(0.000)**	(0.056)	(0.028)*
	12	0.0233	0.0466	0.0701	0.0901	0.0306	0.0434	0.0029	0.0043
		(0.022)*	(0.003)**	(0.000)**	(0.000)**	(0.018)*	(0.008)**	(0.089)	(0.060)
	20	0.0635	0.1266	0.0913	0.2269	0.1493	0.1108	0.0258	0.0352
		(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.022)*	(0.016)*
1952 −2001	1	0.1148	0.1079	0.1593	0.1033	0.0941	0.0518	0.0111	0.0026
		(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.035)*	(0.091)
	4	0.1270	0.1056	0.1558	0.0711	0.1260	0.1016	0.0195	0.0280
		(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.025)*	(0.020)*
	12	0.0448	0.0504	0.0861	0.1417	0.0676	0.1111	0.0245	0.0299
		(0.006)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.023)*	(0.019)*
	20	0.0901	0.0487	0.0751	0.0639	0.0841	0.0718	0.0047	0.0013
		(0.000)**	(0.002)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.058)	(0.110)
1936 −1990	1	0.0325	0.0268	0.0510	0.0427	0.0351	0.0287	0.0071	0.0049
		(0.019)*	(0.021)*	(0.000)**	(0.008)**	(0.018)*	(0.022)*	(0.046)*	(0.058)
	4	0.0087	0.0398	0.0662	0.0703	0.0333	0.0534	0.0040	0.0145
		(0.046)*	(0.013)*	(0.000)**	(0.000)**	(0.020)*	(0.000)**	(0.060)	(0.027)*
	12	0.0827	0.0599	0.0827	0.0639	0.0858	0.0535	0.0019	0.0130
		(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.101)	(0.035)*
	20	0.0817	0.0251	0.2098	0.0708	0.1070	0.0242	0.0349	0.0103
		(0.000)**	(0.022)*	(0.000)**	(0.000)**	(0.000)**	(0.023)*	(0.019)*	(0.037)*
1952 −1990	1	0.0947	0.1137	0.0851	0.0799	0.0271	0.0475	0.0062	0.0144
		(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.021)*	(0.000)**	(0.050)*	(0.028)*
	4	0.0892	0.0750	0.0683	0.0579	0.0809	0.0572	0.0233	0.0051
		(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.024)*	(0.058)
	12	0.1210	0.0679	0.1849	0.1499	0.1202	0.0942	0.0584	0.0266
		(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.022)*
	20	0.0711	0.1101	0.2362	0.0633	0.2116	0.0998	0.0957	0.0116
		(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.034)*

Table 2.4a. Predictability of US Excess Returns(monthly)

We estimate regressions of the form $Y_{t+h} = \alpha_h + \beta_h' X_t + \varepsilon_{h,t+h}$ where $Y_{t+h} = (\tau/h)[(y_{t+1} - r_t) + \cdots + (\ y_{t+h} - r_{t+h-1})$ is the annualized h-period excess return for the aggregate stock market, r_t is the risk-free rate from t to $t+1$, and $y_{t+1} - r_t$ is the excess one period return from time t to $t+1$, with instruments z_t being log dividend yields or log earnings yields. T-statistics in parentheses are computed using Newey West(1987) and Hodrick (1992) standard errors. Horizons h are monthly. The test column reports a p-value for the predictictability test under two hypothesises $H2$ and $H2$. Hypothesis $H2$ is $H_0 : E(Y_{t+h}|X_t) = E(Y_{t+h})$ and Hypothesis $H2$ is $H_0 : E(\varepsilon_{t+h}|X_t) = 0$. $^*p < 0.05$.$^{**}p < 0.01$. The time periods are from Jan. 1970 to Dec. 2006.

	k	Univariate Regression $dy12$ (1)NW	(2)HK	Test (1)H1	(2)H2	$ey12$ (1)NW	(2)HK	Test (1)H1	(2)H2
197001 −200612	1	0.1810	0.1341	0.1699	0.0308	−0.4932	−0.4325	0.1699	0.0287
		(2.25)*	(1.21)	(0.000)**	(0.019)*	(−4.02)**	(−1.01)	(0.000)**	(0.021)*
	12	0.1689	0.1256	0.0132	0.0328	−0.5032	−0.4132	0.0105	0.0473
		(2.34)*	(1.90)	(0.034)*	(0.017)*	(−3.47)**	(−1.74)	(0.036)*	(0.000)**
	60	−0.4365	−0.2874	0.0230	0.0641	−0.5025	−0.3389	0.0509	0.0263
		(4.16)**	(1.80)	(0.024)*	(0.000)**	(−5.53)**	(−2.42)	(0.000)**	(0.021)*

Table 2.4b. Predictability of US Excess Returns(Monthly)

We estimate regressions of the form $Y_{t+h} = \alpha_h + \beta_h' X_t + \varepsilon_{h,t+h}$ where $Y_{t+h} = (\tau/h)[(y_{t+1} - r_t) + \cdots + (\ y_{t+h} - r_{t+h-1})$ is the annualized h-period excess return for the aggregate stock market, r_t is the risk-free rate from t to $t+1$, and $y_{t+1} - r_t$ is the excess one period return from time t to $t+1$, with instruments z_t being log dividend yields and risk free rate together. T-statistics in parentheses are computed using Newey West(1987) and Hodrick (1992) standard errors. Horizons h are monthly. The test column reports a p-value for the predictictability test under six hypothesises $H1 - H6$. X_1 represents the short rate r and X_2 represents the dividend yields. Hypothesis $H1$ $(H_0 : E(Y_{t+h}|X_{1t}) = E(Y_{t+h}))$, Hypothesis $H2$ $(H_0 : E(\varepsilon_{t+h}|X_{1t}) = 0)$,Hypothesis $H3$ $(H_0 : E(Y_{t+h}|X_{1t}) = E(Y_{t+h}))$, Hypothesis $H4$ $(H_0 : E(\varepsilon_{t+h}|X_{2t}) = 0)$, Hypothesis $H5$ $(H_0 : E(Y_{t+h}|X_{1t}, X_{2t}) = E(Y_{t+h}))$, Hypothesis $H6$ $(H_0 : E(\varepsilon_{t+h}|X_{1t}, X_{2t}) = 0)$. $^*p < 0.05$.$^{**}p < 0.01$. The time periods are from Jan. 1970 to Dec. 2006.

	k	BivariateRegression r (1)NW	(2)HK	$dy12$ (1)NW	(2)HK	Test (1)H1	(2)H2	(3)H3	(4)H4	(5)H5	(6)H6
197001 −200612	1	−14.084	−11.256	0.1868	0.1589	0.0224	0.0301	0.0359	0.0498	0.0143	0.0144
		(−15.35)**	(−12.60)**	(2.53)*	(1.32)	(0.023)*	(0.019)*	(0.011)*	(0.000)**	(0.032)*	(0.032)*
	12	−0.8856	−0.6328	0.0513	0.0339	0.0448	0.0297	0.0249	0.0320	0.0124	0.0195
		(−10.98)**	(−8.03)**	(0.97)	(0.56)	(0.000)**	(0.020)*	(0.022)*	(0.017)*	(0.035)*	(0.028)*
	60	−0.1326	−0.0927	−0.3782	−0.2734	0.0487	0.0268	0.0230	0.0630	0.0150	0.0134
		(−1.71)	(−0.88)	(2.18)	(1.14)	(0.000)**	(0.022)*	(0.022)*	(0.000)**	(0.029)*	(0.034)*

Table 2.4c. Predictability of US Excess Returns(Monthly)

We estimate regressions of the form $Y_{t+h} = \alpha_h + \beta_h' X_t + \varepsilon_{h,t+h}$ where $Y_{t+h} = (\tau/h)[(y_{t+1} - r_t) + \cdots + (y_{t+h} - r_{t+h-1})$ is the annualized h-period excess return for the aggregate stock market, r_t is the risk-free rate from t to $t+1$, and $y_{t+1} - r_t$ is the excess one period return from time t to $t+1$, with instruments z_t being log dividends yields and log earnings yields together. T-statistics in parentheses are computed using Newey West(1987) and Hodrick (1992) standard errors. Horizons h are monthly. The test column reports a p-value for the predictictability test under six hypothesises $H1 - H6$. X_1 represents the short rate r and X_2 represents the earnings yields. Hypothesis $H1$ ($H_0 : E(Y_{t+h}|X_{1t}) = E(Y_{t+h})$), Hypothesis $H2$ ($H_0 : E(\varepsilon_{t+h}|X_{1t}) = 0$),Hypothesis $H3$ ($H_0 : E(Y_{t+h}|X_{1t}) = E(Y_{t+h})$), Hypothesis $H4$ ($H_0 : E(\varepsilon_{t+h}|X_{2t}) = 0$), Hypothesis $H5$ ($H_0 : E(Y_{t+h}|X_{1t}, X_{2t}) = E(Y_{t+h})$), Hypothesis $H6$ ($H_0 : E(\varepsilon_{t+h}|X_{1t}, X_{2t}) = 0$). $^{*}p < 0.05.^{**}p < 0.01$.The time periods are from Jan. 1970 to Dec. 2006.

		BivariateRegression				Test					
	k	$dy12$ (1)NW	(2)HK	$ey12$ (1)NW	(2)HK	(1)H1	(2)H2	(3)H3	(4)H4	(5)H5	(6)H6
197001 −200612	1	−14.783	−11.215	0.2395	0.1945	0.0224	0.0250	0.0311	0.0352	0.0114	0.0897
		$(-13.63)^{**}$	$(-16.34)^{**}$	$(2.53)^{*}$	(1.45)	$(0.023)^{*}$	$(0.022)^{*}$	$(0.020)^{*}$	$(0.015)^{*}$	$(0.034)^{*}$	$(0.000)^{**}$
	12	−0.8311	−0.6834	−0.0099	−0.0043	0.0448	0.0450	0.0209	0.0475	0.0120	0.0241
		$(-9.23)^{**}$	$(-6.80)^{**}$	(0.15)	(0.00)	$(0.000)^{**}$	$(0.000)^{**}$	$(0.025)^{*}$	$(0.000)^{**}$	$(0.032)^{*}$	$(0.022)^{*}$
	60	0.0879	0.0632	−0.5493	−0.4222	0.0497	0.0267	0.0509	0.0306	0.0177	0.0137
		(1.07)	(0.54)	(1.74)	(0.35)	$(0.000)^{**}$	$(0.021)^{*}$	$(0.000)^{**}$	$(0.021)^{*}$	$(0.030)^{*}$	$(0.031)^{*}$

Table 2.4d. Predictability of US Excess Returns(Monthly)

(a)We estimate regressions of the form $Y_{t+h} = \alpha_h + \beta_h' X_t + \varepsilon_{h,t+h}$ where $Y_{t+h} = (\tau/h)[(y_{t+1} - r_t) + \cdots + (y_{t+h} - r_{t+h-1})$ is the annualized h-period excess return for the aggregate stock market, r_t is the risk-free rate from t to $t+1$, and $y_{t+1} - r_t$ is the excess one period return from time t to $t+1$, with instruments z_t being short rate, log dividends yields, and log earnings yields together. T-statistics in parentheses are computed using Newey West(1987) and Hodrick (1992) standard errors. Horizons h are monthly. The time periods are from Jan. 1970 to Dec. 2006. (b)The test column reports a p-value for the predictictability test under six hypothesises $H1 - H8$. X_1 represents the short rate r , X_2 represents the dividends yields and X_3 represents the earnings yields. Hypothesis $H1$ ($H_0 : E(Y_{t+h}|X_{1t}) = E(Y_{t+h})$), Hypothesis $H2$ ($H_0 : E(\varepsilon_{t+h}|X_{1t}) = 0$),Hypothesis $H3$ ($H_0 : E(Y_{t+h}|X_{1t}) = E(Y_{t+h})$), Hypothesis $H4$ ($H_0 : E(\varepsilon_{t+h}|X_{2t}) = 0$), Hypothesis $H5$ ($H_0 : E(Y_{t+h}|X_{3t}) = E(Y_{t+h})$), Hypothesis $H6$ ($H_0 : E(\varepsilon_{t+h}|X_{3t}) = 0$),Hypothesis $H7$ ($H_0 : E(Y_{t+h}|X_{1t}, X_{2t}, X_{3t}) = E(Y_{t+h})$), Hypothesis $H8$ ($H_0 : E(\varepsilon_{t+h}|X_{1t}, X_{2t}, X_{3t}) = 0$). $^{*}p < 0.05.^{**}p < 0.01$.

Panel a		BivariateRegression					
	k	r (1)NW	(2)HK	$dy4$ (1)NW	(2)HK	$ey4$ (1)NW	(2)HK
197001 −200612	1	−14.799	−10.498	−0.0505	−0.0228	0.1930	0.1590
		$(-13.69)^{**}$	$(-10.83)^{**}$	(0.49)	(0.12)	(1.42)	(0.98)
	12	−0.8328	−0.5639	0.1814	0.1434	−0.1779	−0.1034
		$(-9.53)^{**}$	$(-6.34)^{**}$	$(2.42)^{*}$	(1.23)	(−1.85)	(−0.70)
	60	0.1111	0.7381	0.1467	0.1031	−0.6974	−0.4723
		(1.32)	(0.46)	$(2.05)^{*}$	(1.37)	$(-6.62)^{**}$	$(-2.12)^{*}$

Panel b		Test							
		(1)H1	(2)H2	(3)H3	(4)H4	(5)H5	(6)H6	(7)H7	(8)H8
197001 −200612	1	0.0224	0.0290	0.0359	0.0376	0.0311	0.0620	0.0116	0.0093
		$(0.023)^{*}$	$(0.019)^{*}$	$(0.012)^{*}$	$(0.008)^{**}$	$(0.020)^{*}$	$(0.000)^{**}$	$(0.034)^{*}$	$(0.044)^{*}$
	12	0.0448	0.0569	0.0249	0.0624	0.0209	0.0486	0.0087	0.0100
		$(0.000)^{**}$	$(0.000)^{**}$	$(0.022)^{*}$	$(0.000)^{**}$	$(0.025)^{*}$	$(0.000)^{**}$	$(0.045)^{*}$	$(0.042)^{*}$
	60	0.0487	0.0693	0.0230	0.0154	0.0509	0.0558	0.0020	0.0134
		$(0.000)^{**}$	$(0.000)^{**}$	$(0.021)^{*}$	$(0.028)^{*}$	$(0.000)^{**}$	$(0.000)^{**}$	(0.081)	$(0.031)^{*}$

Table 2.5. Predictability of US Excess Returns(Annually)

We estimate regressions of the form $Y_{t+h} = \alpha_h + \beta_h' X_t + \varepsilon_{h,t+h}$ where $Y_{t+h} = (\tau/h)[(y_{t+1} - r_t) + \cdots + (y_{t+h} - r_{t+h-1})]$ is the annualized h-period excess return for the aggregate stock market, r_t is the risk-free rate from t to $t+1$, and $y_{t+1} - r_t$ is the excess one period return from time t to $t+1$, with instruments z_t being log dividend yields, log earnings yields, dividend payout ratio, short rate, inflation, book-to-market ratio(b/m), investment to capital ratio(i/k), corporate issuing activity (Eqis and Ntis), and consumption, wealth, and income ratio(cay). T-statistics in parentheses are computed using Newey West(1987) and Hodrick (1992) standard errors. Horizons h are anuually. The test column reports a p-value for the predictictability test under two hypothesises $H2$ and $H2$. Hypothesis $H2$ is $H_0 : E(Y_{t+h}|X_t) = E(Y_{t+h})$ and Hypothesis $H2$ is $H_0 : E(\varepsilon_{t+h}|X_t) = 0$. $^*p < 0.05$.$^{**}p < 0.01$. In order to compare the prevailing predictive models with the historical mean model, we define a new variable $\Delta(\frac{Q_h}{\sigma^2}) = \hat{Q}_N(h)/\widehat{\sigma}^2_\varepsilon - \hat{Q}_A(h)/\widehat{\sigma}^2_\varepsilon$, where $\hat{Q}_N(h)/\widehat{\sigma}^2_\varepsilon$ is computed by the historical mean model and $\hat{Q}_A(h)/\widehat{\sigma}^2_\varepsilon$ is computed by the prevailing predictive regression model. We also compute the IS $\overline{R}^2$, OOS $\overline{R}^2$, and $\Delta RMSE$ following the Goyal and Welch (2007)'s definition. The table summarizes the results for both in-sample and out-of-sample tests.

Variable	Data	k	Univariate Regression (1) NW	(2) HK	Test(IS) (1) H1	Test(IS) (2) H2	Test(OS) (1) H1	Test(OS) (2) H2	(1) $\Delta(\frac{Q_h}{\sigma^2})$	(2) $\Delta(\frac{Q_h}{\sigma^2})$	GW IS $\overline{R}^2$	GW OOS $\overline{R}^2$	GW $\Delta RMSE$ (%)
dy	1872 −2005	1	0.0795 (2.07)*	0.0783 (1.65)	0.0674 (0.000)**	0.0328 (0.019)*	0.1613 (0.000)**	0.0753 (0.000)**	0.0367	0.0058	0.91	−1.93	−0.10
		5	0.0665 (1.60)	0.0634 (1.04)	0.0401 (0.014)*	0.0430 (0.011)*	0.0963 (0.000)**	0.0921 (0.000)**	0.0233	0.0183	6.04	−4.45	−0.68
ey	1872 −2005	1	0.0527 (1.14)	0.0478 (0.78)	0.0861 (0.000)**	0.0494 (0.008)**	0.1266 (0.000)**	0.0238 (0.023)*	0.0714	0.0515	1.08	−1.78	−0.08
		5	0.0344 (0.80)	0.0302 (0.46)	0.1055 (0.000)**	0.0855 (0.000)**	0.1030 (0.000)**	0.1081 (0.000)**	0.0300	0.0343	6.24	−1.04	−0.03
d/e	1872 −2005	1	0.0759 (1.46)	0.0696 (1.12)	0.0180 (0.028)*	0.0451 (0.009)**	0.0760 (0.000)**	0.0988 (0.000)**	0.0486	0.0235	−0.75	−4.33	−0.31
		5	0.0698 (1.55)	0.0589 (0.89)	0.0298 (0.021)*	0.0361 (0.018)*	0.0938 (0.000)**	0.0955 (0.000)**	0.0208	0.0217	0.66	−4.87	−0.76
r	1872 −2005	1	−0.7299 (−1.95)*	−0.6545 (−0.98)	0.0232 (0.024)*	0.0409 (0.010)**	0.1057 (0.010)**	0.0706 (0.000)**	0.0189	0.0011	0.34	−3.37	−0.14
		5	−0.5524 (−1.02)	−0.4982 (−0.76)	0.0340 (0.019)*	0.0343 (0.019)*	0.1145 (0.010)**	0.1004 (0.000)**	0.0415	0.0266	3.83	−17.66	−2.78
infl	1919 −2005	1	−0.3766 (−1.18)	−0.3121 (−0.87)	0.0409 (0.010)**	0.1088 (0.010)**	0.0064 (0.052)	0.0563 (0.000)**	0.1182	0.0132	−1.00	−4.07	−0.20
		5	−0.4034 (−1.00)	−0.3441 (−0.49)	0.1145 (0.000)**	0.1001 (0.000)**	0.0877 (0.000)**	0.0876 (0.000)**	0.0147	0.0138	−1.21	−11.25	−1.70
b/m	1921 −2005	1	0.0641 (1.56)	0.0546 (1.12)	0.0352 (0.018)*	0.1014 (0.000)**	0.0629 (0.000)**	0.1436 (0.000)**	0.0617	0.0741	3.20	−1.72	−0.01
		5	0.0182 (0.46)	0.0124 (0.21)	0.1317 (0.000)**	0.1267 (0.000)**	0.1413 (0.000)**	0.1324 (0.000)**	0.0683	0.0586	10.78	−13.06	−2. − 03
i/k	1947 −2005	1	0.0355 (0.66)	0.0312 (0.40)	0.1213 (0.000)**	0.1035 (0.000)**	0.3574 (0.000)**	0.4443 (0.000)**	0.2328	0.3748	6.63	−1.77	0.07
		5	0.0256 (0.40)	0.0212 (0.21)	0.0799 (0.000)**	0.0821 (0.000)**	0.1156 (0.000)**	0.0732 (0.000)**	0.0426	0.0006	33.99	12.99	3.39
ntis	1927 −2005	1	0.1833 (0.67)	0.1645 (0.34)	0.0177 (0.028)*	0.0265 (0.021)*	0.0034 (0.072)	0.0234 (0.023)*	0.1212	0.0461	8.15	−5.07	−0.26
		5	0.1754 (0.65)	0.1437 (0.45)	0.0729 (0.000)**	0.0726 (0.000)**	0.0218 (0.025)*	0.0060 (0.046)*	0.0512	0.0678	6.59	−3.46	−0.32
eqis	1927 −2005	1	−0.1125 (−2.98)*	−0.0937 (−1.60)	0.0464 (0.005)**	0.0426 (0.008)**	0.1137 (0.000)**	0.0670 (0.000)**	0.0109	0.0025	9.15	2.04	0.30
		5	−0.0515 (−1.26)	−0.0332 (−0.90)	0.1598 (0.000)**	0.1599 (0.000)**	0.1013 (0.000)**	0.0813 (0.000)**	0.0283	0.0075	9.50	−2.35	−0.11
cay	1945 −2005	1	0.0529 (4.08)**	0.0445 (3.68)**	0.0128 (0.036)*	0.1121 (0.000)**	0.0066 (0.043)*	0.1538 (0.000)**	0.1194	0.0843	15.72	16.78	1.61
		5	0.0133 (1.11)	0.0092 (0.86)	0.1085 (0.000)**	0.1055 (0.000)**	0.1451 (0.000)**	0.1647 (0.000)**	0.0721	0.0909	36.05	30.35	7.50

Table 2.6a. Equity Premium Out-of-Sample Forecasting Results(Univariate, Quarterly)

Table 6 show the out-of-sample results of the univariate linear predictive models. Table 6a summarize the MSE, MAE, and RMSE of linear predictive regression for dividend yield and earning yield during the period 1936-2001, and 1952-2001. The benchmark model is historical average equity returns. The alternative models are linear predictive model and two nonparametric predictive models. Table 6a summarize the statistical results of univariate linear predictive regression for dividend yield and earning yield by using the measure MSE, MAE, and RMSE during the period 1936-2001, and1952-2001.

				HMM	LPM	NPM1	NPM2				HMM	LPM	NPM1	NPM2
1936 −2001	$dy4$	1	MSE	0.1389	0.1481	|0.1444	0.1262	$ey4$	1	MSE	0.1389	0.1658	0.1469	0.1259
			MAE	0.2881	0.2803	0.2889	0.2728			MAE	0.2881	0.2972	0.2967	0.2718
			$RMSE$	0.3726	0.3848	0.3799	0.3553			$RMSE$	0.3726	0.4072	0.3833	0.3549
		4	MSE	0.0546	0.0629	0.0576	0.0388		4	MSE	0.0739	0.1005	0.0825	0.0593
			MAE	0.1733	0.1925	0.1897	0.1568			MAE	0.2061	0.2497	0.2243	0.1872
			$RMSE$	0.2336	0.2508	0.2399	0.1970			$RMSE$	0.2713	0.3170	0.2872	0.2436
		12	MSE	0.0297	0.0384	0.0281	0.0136		12	MSE	0.0563	0.0778	0.0593	0.0397
			MAE	0.1423	0.1642	0.1304	0.0939			MAE	0.1893	0.2324	0.1801	0.1406
			$RMSE$	0.1723	0.1961	0.1678	0.1168			$RMSE$	0.2372	0.2789	0.2435	0.1992
		20	MSE	0.0146	0.0380	0.0352	0.0115		20	MSE	0.0537	0.0744	0.0539	0.0377
			MAE	0.1042	0.1665	0.1605	0.0875			MAE	0.1861	0.2330	0.1697	0.1326
			$RMSE$	0.1208	0.1950	0.1876	0.1071			$RMSE$	0.2318	0.2727	0.2323	0.1942
1952 −2001	$dy4$	1	MSE	0.1260	0.1652	0.1613	0.1225	$ey4$	1	MSE	0.1260	0.1355	0.1341	0.1081
			MAE	0.2604	0.2996	0.3024	0.2679			MAE	0.2604	0.2772	0.2864	0.2531
			$RMSE$	0.3549	0.4065	0.4017	0.3500			$RMSE$	0.3549	0.3680	0.3662	0.3288
		4	MSE	0.0435	0.0738	0.0623	0.0358		4	MSE	0.0435	0.0695	0.0661	0.0344
			MAE	0.1589	0.2100	0.1945	0.1490			MAE	0.1589	0.2126	0.2117	0.1480
			$RMSE$	0.2085	0.2716	0.2496	0.1893			$RMSE$	0.2085	0.2637	0.2570	0.1854
		12	MSE	0.0193	0.0453	0.0308	0.0127		12	MSE	0.0193	0.0455	0.0404	0.0148
			MAE	0.1163	0.1783	0.1345	0.0898			MAE	0.1163	0.1741	0.1660	0.0983
			$RMSE$	0.1391	0.2129	0.1755	0.1126			$RMSE$	0.1391	0.2133	0.2010	0.1215
		20	MSE	0.0146	0.0322	0.0167	0.0091		20	MSE	0.0146	0.0208	0.0202	0.0112
			MAE	0.1042	0.1546	0.0989	0.0760			MAE	0.1042	0.1164	0.1140	0.0850
			$RMSE$	0.1208	0.1796	0.1291	0.0952			$RMSE$	0.1208	0.1443	0.1422	0.1057

Table 2.6b. Equity Premium Out-of-Sample Forecasting Results(Univariate, Quarterly)

Table 6 show the out-of-sample results of the univariate linear predictive models. Table 6b summarize the MSE, MAE, and RMSE of linear predictive regression for dividend yield and earning yield during the period 1936-1990, and 1952-1990. The benchmark model is historical average equity returns. The alternative models are linear predictive model and two nonparametric predictive models. Table 6b summarize the statistical results of univariate linear predictive regression for dividend yield and earning yield by using the measure MSE, MAE, and RMSE during the period 1936-1990, and1952-1990.

				HMM	LPM	NPM1	NPM2				HMM	LPM	NPM1	NPM2
1936 −1990	$dy4$	1	MSE	0.1465	0.1515	|0.1256	0.1253	$ey4$	1	MSE	0.1465	0.1738	0.1364	0.1280
			MAE	0.2719	0.2780	0.2752	0.2725			MAE	0.2719	0.3026	0.2894	0.2761
			$RMSE$	0.3829	0.3892	0.3544	0.3539			$RMSE$	0.3829	0.4169	0.3693	0.3577
		4	MSE	0.0597	0.0649	0.0396	0.0362		4	MSE	0.0597	0.0872	0.0479	0.0370
			MAE	0.1873	0.1894	0.1592	0.1502			MAE	0.1873	0.2279	0.1743	0.1515
			$RMSE$	0.2443	0.2547	0.1990	0.1904			$RMSE$	0.2443	0.2952	0.2189	0.1924
		12	MSE	0.0361	0.0474	0.0142	0.0100		12	MSE	0.0361	0.0651	0.0211	0.0105
			MAE	0.1665	0.1862	0.0938	0.0805			MAE	0.1665	0.2176	0.1143	0.0827
			$RMSE$	0.1900	0.2176	0.1191	0.0999			$RMSE$	0.1900	0.2552	0.1452	0.1024
		20	MSE	0.0346	0.0401	0.0123	0.0093		20	MSE	0.0346	0.0639	0.0116	0.0059
			MAE	0.1724	0.1687	0.0885	0.0798			MAE	0.1724	0.2295	0.0835	0.0624
			$RMSE$	0.1861	0.2002	0.1108	0.0965			$RMSE$	0.1861	0.2528	0.1077	0.0768
1952 −1990	$dy4$	1	MSE	0.1520	0.2018	0.1481	0.1464	$ey4$	1	MSE	0.1520	0.1738	0.1318	0.1247
			MAE	0.2861	0.3357	0.3077	0.2997			MAE	0.2861	0.3129	0.2894	0.2786
			$RMSE$	0.3898	0.4492	0.3848	0.3826			$RMSE$	0.3898	0.4168	0.3630	0.3531
		4	MSE	0.0552	0.1054	0.0453	0.0411		4	MSE	0.0552	0.0923	00462	0.0357
			MAE	0.1798	0.2631	0.1664	0.1569			MAE	0.1798	0.2414	0.1665	0.1467
			$RMSE$	0.2349	0.3246	0.2128	0.2026			$RMSE$	0.2349	0.3039	0.2149	0.1890
		12	MSE	0.0234	0.0660	0.0185	0.0098		12	MSE	0.0234	0.0572	0.0204	0.0111
			MAE	0.1248	0.2204	0.1116	0.0811			MAE	0.1248	0.1950	0.1214	0.0876
			$RMSE$	0.1529	0.2569	0.1362	0.0989			$RMSE$	0.1529	0.2393	0.1427	0.1054
		20	MSE	0.0163	0.0489	0.0096	0.0058		20	MSE	0.0163	0.0340	0.0101	0.0078
			MAE	0.1084	0.1994	0.0844	0.0661			MAE	0.1084	0.1578	0.0911	0.0794
			$RMSE$	0.1278	0.2212	0.0978	0.0763			$RMSE$	0.1278	0.1843	0.1003	0.0883

Table 2.7a. Equity Premium Out-of-Sample Forecasting Results(Bivariate, Quarterly)

Table 7 show the out-of-sample results of the bivariate linear predictive models using quarterly data. Table 7a summarize the MSE, MAE, and RMSE of linear predictive regression for dividend yield and earning yield during the period 1936-2001, and 1952-2001. The benchmark model is historical average equity returns. The alternative models are linear predictive model and two nonparametric predictive models. Table 7a summarize the statistical results of bivariate linear predictive regression for dividend yield and earning yield by using the measure MSE, MAE, and RMSE during the period 1936-2001, and1952-2001.

				HMM	LPM	NPM1	NPM2				HMM	LPM	NPM1	NPM2
1936 −2001	$dy4,r$	1	MSE	0.1389	0.1344	0.1310	0.1226	$ey4,r$	1	MSE	0.1389	0.1592	0.1443	0.1236
			MAE	0.2681	0.2705	0.2762	0.2701			MAE	0.2681	0.2917	0.2933	0.2705
			$RMSE$	0.3726	0.3667	0.3619	0.3501			$RMSE$	0.3726	0.3990	0.3799	0.3516
		4	MSE	0.0734	0.0877	0.0699	0.0375		4	MSE	0.0734	0.0917	0.0816	0.0580
			MAE	0.2048	0.2307	0.2098	0.1553			MAE	0.2048	0.2371	0.2210	0.1852
			$RMSE$	0.2710	0.2962	0.2643	0.1936			$RMSE$	0.2710	0.3028	0.2857	0.2407
		12	MSE	0.0540	0.0289	0.0227	0.0130		12	MSE	0.0540	0.0697	0.0598	0.0388
			MAE	0.1860	0.1397	0.1198	0.0915			MAE	0.1860	0.2182	0.1797	0.1386
			$RMSE$	0.2324	0.1700	0.1508	0.1141			$RMSE$	0.2324	0.2640	0.2445	0.1971
		20	MSE	0.0538	0.0145	0.0128	0.0093		20	MSE	0.0538	0.0632	0.0558	0.0370
			MAE	0.1893	0.0988	0.0915	0.0782			MAE	0.1893	0.2126	0.1742	0.1305
			$RMSE$	0.2320	0.1203	0.1130	0.0963			$RMSE$	0.2320	0.2514	0.2362	0.1923
1952 −2001	$dy4,r$	1	MSE	0.1076	0.1445	0.1153	0.1050	$ey4,r$	1	MSE	0.1076	0.2652	0.2466	0.1058
			MAE	0.2460	0.3003	0.2603	0.2508			MAE	0.2460	0.3864	0.3807	0.2511
			$RMSE$	0.3280	0.3802	0.3395	0.3240			$RMSE$	0.3280	0.5149	0.4966	0.3252
		4	MSE	0.0355	0.0690	0.0568	0.0332		4	MSE	0.0355	0.1473	0.1415	0.0335
			MAE	0.1471	0.2143	0.1897	0.1454			MAE	0.1471	0.2863	0.3030	0.1462
			$RMSE$	0.1885	0.2627	0.2383	0.1822			$RMSE$	0.1885	0.3837	0.3761	0.1830
		12	MSE	0.0179	0.0300	0.0283	0.0142		12	MSE	0.0179	0.0541	0.0550	0.0144
			MAE	0.1090	0.1404	0.1347	0.0964			MAE	0.1090	0.1804	0.1831	0.0969
			$RMSE$	0.1340	0.1733	0.1681	0.1190			$RMSE$	0.1340	0.2326	0.2345	0.1201
		20	MSE	0.0126	0.0196	0.0171	0.0110		20	MSE	0.0126	0.0279	0.0270	0.0111
			MAE	0.0930	0.1246	0.1101	0.0858			MAE	0.0930	0.1439	0.1395	0.0863
			$RMSE$	0.1124	0.1402	0.1309	0.1047			$RMSE$	0.1124	0.1670	0.1643	0.1055

Table 2.7b. Equity Premium Out-of-Sample Forecasting Results(Bivariate, Quarterly)

Table 2.7 show the out-of-sample results of the bivariate linear predictive models using quarterly data. Table 7a summarize the MSE, MAE, and RMSE of linear predictive regression for dividend yield and earning yield during the period 1936-2001, and 1952-2001. The benchmark model is historical average equity returns. The alternative models are linear predictive model and two nonparametric predictive models. Table 7b summarize the statistical results of bivariate linear predictive regression for dividend yield and earning yield by using the measure MSE, MAE, and RMSE during the period 1936-1990, and1952-1990.

				HMM	LPM	NPM1	NPM2				HMM	LPM	NPM1	NPM2
1936 −1990	$dy4, r$	1	MSE	0.1692	0.1378	0.1177	0.1210	$ey4, r$	1	MSE	0.1692	0.1733	0.1281	0.1217
			MAE	0.2999	0.2664	0.2669	0.2699			MAE	0.2999	0.3028	0.2796	0.2702
			$RMSE$	0.4114	0.3722	0.3431	0.3479			$RMSE$	0.4114	0.4163	0.3679	0.3488
		4	MSE	0.0710	0.1839	0.0698	0.0352		4	MSE	0.0710	0.0803	0.0432	0.0356
			MAE	0.2050	0.3450	0.2047	0.1483			MAE	02050	0.2156	0.1663	0.1491
			$RMSE$	0.2664	0.4288	0.2642	0.1877			$RMSE$	0.2664	0.2834	0.2079	0.1886
		12	MSE	0.0403	0.0885	0.0222	0.0097		12	MSE	0.0403	0.0599	0.0171	0.0098
			MAE	0.1758	0.2596	0.1120	0.0793			MAE	0.1758	0.2102	0.1027	0.0794
			$RMSE$	0.2006	0.2976	0.1491	0.0986			$RMSE$	0.2006	0.2449	0.1309	0.0988
		20	MSE	0.0384	0.0382	0.0078	0.0057		20	MSE	0.0384	0.0490	0.0098	0.0058
			MAE	0.1801	0.1747	0.0685	0.0621			MAE	0.1801	0.1987	0.0767	0.0622
			$RMSE$	0.1959	0.1954	0.0883	0.0758			$RMSE$	0.1959	0.2214	0.0991	0.0762
1952 −1990	$dy4, r$	1	MSE	0.1388	0.1270	0.1245	0.1358	$ey4, r$	1	MSE	0.1388	0.1421	0.1258	0.1198
			MAE	0.2572	0.2782	0.2713	0.2909			MAE	0.2572	0.2831	0.2886	0.2755
			$RMSE$	0.3726	0.3563	0.3528	0.3685			$RMSE$	0.3726	0.3769	0.3547	0.3462
		4	MSE	0.0552	0.0393	0.0328	0.0384		4	MSE	0.0552	0.0639	0.0441	0.0344
			MAE	0.1798	0.1583	0.1469	0.1519			MAE	0.1798	0.1999	0.1696	0.1436
			$RMSE$	0.2349	0.1981	0.1811	0.1960			$RMSE$	0.2349	0.2527	0.2101	0.1855
		12	MSE	0.0234	0.0218	0.0122	0.0093		12	MSE	0.0234	0.0357	0.0122	0.0095
			MAE	0.1248	0.1166	0.0908	0.0789			MAE	0.1248	0.1572	0.0918	0.0796
			$RMSE$	0.1529	0.1477	0.1106	0.0963			$RMSE$	0.1529	0.1889	0.1106	0.0973
		20	MSE	0.0163	0.0141	0.0135	0.0047		20	MSE	0.0163	0.0383	0.0080	0.0056
			MAE	0.1084	0.0995	0.0963	0.0576			MAE	0.1084	0.1744	0.0763	0.0654
			$RMSE$	0.1278	0.1189	0.1163	0.0688			$RMSE$	0.1278	0.1958	0.0896	0.0751

Table 2.8. Equity Premium Out-of-Sample Forecasting Results (Annually)

Table 2.8 summarize the out-of-sample results of univariate linear predictive regression for dividend yield and earning yield by using the measure MSE, MAE, and RMSE annually. The predictors are dividend yield (D/Y), earnings-price ratio (E/P), dividend-payout ratio (D/E), book-to-market ratio (B/M), net equity expansion ($NTIS$), treasure bill rate (TBL), Percent Equity Issuing ($eqis$), Consumption income wealth ratio (Cay), inflation ($INFL$), and investment-to-capital ratio (I/K) during the period 1972 and 2005. The benchmark model is historical average equity returns. The alternative models are linear predictive model and two nonparametric predictive models.

				HMM	LPM	NPM1	NPM2					HMM	LPM	NPM1	NPM2
dy	1872	1	MSE	0.0261	0.0268	0.0261	0.0250	b/m	1921	1	MSE	0.0263	0.0385	0.0410	0.0243
	−2005		MAE	0.1238	0.1284	0.1271	0.1263		−2005		MAE	0.1230	0.1531	0.1568	0.1227
			$RMSE$	0.1615	0.1640	0.1617	0.1581				$RMSE$	0.1621	0.1962	0.2025	0.1559
		5	MSE	0.0249	0.0237	0.0239	0.0236			5	MSE	0.0267	0.0267	0.0279	0.0250
			MAE	0.1221	0.1220	0.1224	0.1148				MAE	0.1251	0.1291	0.1327	0.1275
			$RMSE$	0.1578	0.1540	0.1547	0.1535				$RMSE$	0.1635	0.1633	0.1672	0.1580
ey	1872	1	MSE	0.0261	0.0293	0.0285	0.0259	i/k	1947	1	MSE	0.0257	0.0332	0.0244	0.0227
	−2005		MAE	0.1238	0.1331	0.1355	0.1298		−2005		MAE	0.1213	0.1637	0.1252	0.1226
			$RMSE$	0.1615	0.1711	0.1687	0.1608				$RMSE$	0.1604	0.1822	0.1561	0.1507
		5	MSE	0.0249	0.0233	0.0216	0.0207			5	MSE	0.0266	0.0285	0.0264	0.0259
			MAE	0.1221	0.1199	0.1174	0.1101				MAE	0.1250	0.1476	0.1335	0.1328
			$RMSE$	0.1578	0.1528	0.1469	0.1439				$RMSE$	0.1630	0.1689	0.1625	0.1609
d/e	1872	1	MSE	0.0261	0.0264	0.0262	0.0243	ntis	1927	1	MSE	0.0268	0.0317	0.0261	0.0257
	−2005		MAE	0.1238	0.1255	0.1249	0.1186		−2005		MAE	0.1253	0.1578	0.1338	0.1337
			$RMSE$	0.1615	0.1624	0.1620	0.1558				$RMSE$	0.1637	0.1780	0.1615	0.1604
		5	MSE	0.0249	0.0233	0.0216	0.0207			5	MSE	0.0262	0.0297	0.0277	0.0277
			MAE	0.1221	0.1199	0.1174	0.1101				MAE	0.1239	0.1281	0.1330	0.1331
			$RMSE$	0.1578	0.1528	0.1469	0.1439				$RMSE$	0.1618	0.1722	0.1663	0.1665
r	1872	1	MSE	0.0261	0.0268	0.0261	0.0237	eqis	1927	1	MSE	0.0253	0.0262	0.0248	0.0248
	−2005		MAE	0.1238	0.1284	0.1267	0.1194		−2005		MAE	0.1205	0.1201	0.1262	0.1263
			$RMSE$	0.1615	0.1636	0.1614	0.1539				$RMSE$	0.1591	0.1620	0.1575	0.1577
		5	MSE	0.0249	0.0237	0.0256	0.0236			5	MSE	0.0262	0.0330	0.0262	0.0253
			MAE	0.1221	0.1216	0.1252	0.1182				MAE	0.1239	0.1377	0.1269	0.1249
			$RMSE$	0.1578	0.1539	0.1602	0.1535				$RMSE$	0.1618	0.1816	0.1618	0.1589
infl	1919	1	MSE	0.0249	0.0307	0.0251	0.0239	cay	1945	1	MSE	0.0249	0.0276	0.0231	0.0210
	−2005		MAE	0.1181	0.1308	0.1288	0.1247		−2005		MAE	0.1215	0.1296	0.1158	0.1166
			$RMSE$	0.1577	0.1753	0.1584	0.1547				$RMSE$	0.1578	0.1660	0.1521	0.1450
		5	MSE	0.0268	0.0368	0.0264	0.0257			5	MSE	0.0206	0.0257	0.0247	0.0240
			MAE	0.1242	0.1479	0.1337	0.1271				MAE	0.1191	0.1296	0.1265	0.1329
			$RMSE$	0.1638	0.1917	0.1625	0.1603				$RMSE$	0.1436	0.1604	0.1573	0.1549

Table 2.9. Equity Premium Out-of-Sample Forecasting Results for Combining Methods (Annually)

Table 2.9 report the equity premium out-of-sample combined forecasting results using the annual data. The combination forecasts of Y_{t+1} made at time t are weighted averages of the M individual forecasts based on $\widehat{Y}_{c,t+h} = \sum_{i=1}^{M} \omega_{i,t} \widehat{Y}_{i,t+h}$ where $\{\omega_{i,t}\}_{i=1}^{M}$ are the ex ante combining weights formed at time t, and $\widehat{Y}_{i,t+h}$ is the out-of-sample forecast of the equity premium based on the individual predictive models. The first three methods use simple averaging schemes: mean, median, and trimmed mean. Their discount mean square prediction error ($DMSPE$) combining method employs the following weights: $w_{i,t} = \phi_{i,t}^{-1} / \sum_{j=1}^{M} \phi_{j,t}^{-1}, \phi_{i,t} = \sum_{s=R}^{t-1} \theta^{t-1-s} (Y_{i,t+h} - \widehat{Y}_{i,t+h})^2$ and θ is a discount factor. We consider the two values of 1.0 and 0.9 for θ.

	OS			HMM	LPM	NPM1	NPM2		OS			HMM	LPM	NPM1	NPM2
Mean	1965 −2005	1	MSE	0.0261	0.0244	0.0251	0.0239	DMSPE $\theta = 1.0$	1965 −2005	1	MSE	0.0261	0.0246	0.0256	0.0240
			MAE	0.1238	0.1205	0.1217	0.1206				MAE	0.1238	0.1214	0.1239	0.1212
			$RMSE$	0.1615	0.1563	0.1585	0.1545				$RMSE$	0.1615	0.1568	0.1599	0.1549
		5	MSE	0.0249	0.0240	0.0219	0.0215			5	MSE	0.0249	0.0266	0.0252	0.0214
			MAE	0.1221	0.1168	0.1114	0.1174				MAE	0.1221	0.1275	0.1247	0.1164
			$RMSE$	0.1578	0.1548	0.1479	0.1466				$RMSE$	0.1578	0.1632	0.1589	0.1463
Median	1965 −2005	1	MSE	0.0261	0.0233	0.0249	0.0230	DMSPE $\theta = 0.9$	1965 −2005	1	MSE	0.0261	0.0248	0.0260	0.0240
			MAE	0.1238	0.1169	0.1190	0.1170				MAE	0.1238	0.1220	0.1248	0.1211
			$RMSE$	0.1615	0.1528	0.1578	0.1517				$RMSE$	0.1615	0.1575	0.1613	0.1549
		5	MSE	0.0249	0.0256	0.0213	0.0213			5	MSE	0.0249	0.0303	0.0288	0.0214
			MAE	0.1221	0.1195	0.1109	0.1178				MAE	0.1221	0.1355	0.1332	0.1162
			$RMSE$	0.1578	0.1600	0.1458	0.1460				$RMSE$	0.1578	0.1740	0.1698	0.1462
Trimmed Mean	1965 −2005	1	MSE	0.0261	0.0243	0.0248	0.0233								
			MAE	0.1238	0.1200	0.1200	0.1187								
			$RMSE$	0.1615	0.1557	0.1575	0.1526								
		5	MSE	0.0249	0.0244	0.0217	0.0213								
			MAE	0.1221	0.1171	0.1117	0.1161								
			$RMSE$	0.1578	0.1562	0.1471	0.1461								

Table 2.10. Equity Premium Out-of-Sample Forecasting Results (Quarterly)

Table 2.10 report the equity premium out-of-sample forecasting results using the quarterly data from 1947:1–2007:4. The out-of-sample forecast evaluation periods are 1965:1–2007:4 consistent with Goyal and Welch (2008). Table 8 summarize the MSE, MAE, and RMSE of linear predictive regression for dividend-price ratio (D/P), dividend yield (D/Y), earnings-price ratio (E/P), dividend-payout ratio (D/E), stock variance ($SVAR$), book-to-market ratio (B/M), net equity expansion ($NTIS$), treasure bill rate (TBL), long-term yield (LTY), long-term return (LTR), term spread (TMS), default yield spread (DFY), default return yield (DFR), inflation ($INFL$), and investment-to-capital ratio (I/K). The benchmark model is historical average equity returns. The alternative models are linear predictive model and two nonparametric predictive models.

			HMM	LPM	NPM1	NPM2				HMM	LPM	NPM1	NPM2
1965:1	–2007:4												
D/P	1	*MSE*	0.0402	0.0548	0.0466	0.0331	LTY	1	*MSE*	0.0402	0.0475	0.0318	0.0315
		MAE	0.1469	0.1720	0.1659	0.1397			*MAE*	0.1469	0.1791	0.1405	0.1366
		RMSE	0.2004	0.2340	0.2159	0.1819			*RMSE*	0.2004	0.2181	0.1782	0.1776
	4	*MSE*	0.0235	0.0380	0.0301	0.0157		4	*MSE*	0.0235	0.0157	0.0119	0.0115
		MAE	0.1137	0.1499	0.1376	0.0984			*MAE*	0.1137	0.0985	0.0862	0.0851
		RMSE	0.1534	0.1950	0.1734	0.1255			*RMSE*	0.1534	0.1254	0.1090	0.1075
	12	*MSE*	0.0180	0.0318	0.0230	0.0093		12	*MSE*	0.0180	0.0094	0.0072	0.0070
		MAE	0.1099	0.1443	0.1192	0.0753			*MAE*	0.1099	0.0756	0.0706	0.0707
		RMSE	0.1343	0.1783	0.1516	0.0967			*RMSE*	0.1343	0.0969	0.0847	0.0837
D/Y	1	*MSE*	0.0402	0.0546	0.0474	0.0331	LTR	1	*MSE*	0.0402	0.0601	0.0320	0.0310
		MAE	0.1469	0.1708	0.1665	0.1397			*MAE*	0.1469	0.1906	0.1375	0.1353
		RMSE	0.2004	0.2337	0.2176	0.1820			*RMSE*	0.2004	0.2451	0.1789	0.1761
	4	*MSE*	0.0235	0.0378	0.0298	0.0157		4	*MSE*	0.0235	0.0488	0.0171	0.0161
		MAE	0.1137	0.1491	0.1372	0.0985			*MAE*	0.1137	0.1856	0.1005	0.0989
		RMSE	0.1534	0.1944	0.1728	0.1255			*RMSE*	0.1534	0.2210	0.1308	0.1269
	12	*MSE*	0.0180	0.0315	0.0221	0.0093		12	*MSE*	0.0180	0.0353	0.0097	0.0095
		MAE	0.1099	0.1423	0.1174	0.0753			*MAE*	0.1099	0.1632	0.0764	0.0758
		RMSE	0.1343	0.1775	0.1487	0.0965			*RMSE*	0.1343	0.1879	0.0983	0.0976
E/P	1	*MSE*	0.0402	0.0594	0.0432	0.0337	TMS	1	*MSE*	0.0402	0.0879	0.0390	0.0336
		MAE	0.1469	0.1789	0.1591	0.1406			*MAE*	0.1469	0.2434	0.1544	0.1398
		RMSE	0.2004	0.2438	0.2079	0.1835			*RMSE*	0.2004	0.2965	0.1974	0.1833
	4	*MSE*	0.0235	0.0428	0.0269	0.0159		4	*MSE*	0.0235	0.0515	0.0159	0.0135
		MAE	0.1137	0.1544	0.1295	0.0994			*MAE*	0.1137	0.1984	0.0985	0.0933
		RMSE	0.1534	0.2069	0.1641	0.1262			*RMSE*	0.1534	0.2269	0.1263	0.1162
	12	*MSE*	0.0180	0.0361	0.0206	0.0094		12	*MSE*	0.0180	0.0389	0.0095	0.0086
		MAE	0.1099	0.1482	0.1108	0.0755			*MAE*	0.1099	0.1785	0.0754	0.0748
		RMSE	0.1343	0.1899	0.1435	0.0969			*RMSE*	0.1343	0.1973	0.0974	0.0925
D/E	1	*MSE*	0.0402	0.0632	0.0340	0.0335	DFY	1	*MSE*	0.0402	0.0741	0.0364	0.0339
		MAE	0.1469	0.1947	0.1418	0.1409			*MAE*	0.1469	0.2130	0.1464	0.1414
		RMSE	0.2004	0.2515	0.1844	0.1831			*RMSE*	0.2004	0.2723	0.1908	0.1840
	4	*MSE*	0.0235	0.0526	0.0179	0.0159		4	*MSE*	0.0235	0.0581	0.0189	0.0159
		MAE	0.1137	0.1923	0.1040	0.0987			*MAE*	0.1137	0.2015	0.1078	0.0993
		RMSE	0.1534	0.2292	0.1338	0.1262			*RMSE*	0.1534	0.2410	0.1375	0.1262
	12	*MSE*	0.0180	0.0434	0.0114	0.0095		12	*MSE*	0.0180	0.0417	0.0106	0.0094
		MAE	0.1099	0.1819	0.0815	0.0756			*MAE*	0.1099	0.1774	0.0814	0.0756
		RMSE	0.1343	0.2083	0.1069	0.0972			*RMSE*	0.1343	0.2042	0.1030	0.0968

			HMM	LPM	NPM1	NPM2				HMM	LPM	NPM1	NPM2
1965:1	−2007:4												
SVAR	1	MSE	0.0402	0.0672	0.0338	0.0337	DFR	1	MSE	0.0402	0.0591	0.0340	0.0338
		MAE	0.1469	0.1984	0.1438	0.1417			MAE	0.1469	0.1870	0.1419	0.1419
		$RMSE$	0.2004	0.2592	0.1840	0.1837			$RMSE$	0.2004	0.2431	0.1845	0.1840
	4	MSE	0.0235	0.0482	0.0163	0.0161		4	MSE	0.0235	0.0425	0.0161	0.0161
		MAE	0.1137	0.1820	0.1010	0.0994			MAE	0.1137	0.1699	0.0994	0.0994
		$RMSE$	0.1534	0.2194	0.1277	0.1267			$RMSE$	0.1534	0.2063	0.1269	0.1269
	12	MSE	0.0180	0.0388	0.0095	0.0095		12	MSE	0.0180	0.0349	0.0096	0.0095
		MAE	0.1099	0.1723	0.0767	0.0762			MAE	0.1099	0.1619	0.0767	0.0769
		$RMSE$	0.1343	0.1969	0.0976	0.0976			$RMSE$	0.1343	0.1869	0.0978	0.0977
B/M	1	MSE	0.0402	0.0845	0.0815	0.0331	INFL	1	MSE	0.0402	0.0572	0.0338	0.0329
		MAE	0.1469	0.2254	0.2258	0.1397			MAE	0.1469	0.1831	0.1415	0.1355
		$RMSE$	0.2004	0.2907	0.2855	0.1820			$RMSE$	0.2004	0.2392	0.1840	0.1814
	4	MSE	0.0235	0.0718	0.0686	0.0157		4	MSE	0.0235	0.0411	0.0161	0.0156
		MAE	0.1137	0.2243	0.2147	0.0984			MAE	0.1137	0.1667	0.0992	0.0978
		$RMSE$	0.1534	0.2679	0.2619	0.1254			$RMSE$	0.1534	0.2026	0.1271	0.1251
	12	MSE	0.0180	0.0619	0.0572	0.0093		12	MSE	0.0180	0.0361	0.0100	0.0095
		MAE	0.1099	0.2134	0.1984	0.0751			MAE	0.1099	0.1643	0.0769	0.0754
		$RMSE$	0.1343	0.2488	0.2392	0.0964			$RMSE$	0.1343	0.1901	0.0999	0.0975
NTIS	1	MSE	0.0402	0.0580	0.0336	0.0334	I/K	1	MSE	0.0402	0.0457	0.0333	0.0315
		MAE	0.1469	0.1835	0.1412	0.1408			MAE	0.1469	0.1603	0.1402	0.1338
		$RMSE$	0.2004	0.2408	0.1832	0.1827			$RMSE$	0.2004	0.2138	0.1825	0.1774
	4	MSE	0.0235	0.0392	0.0164	0.0159		4	MSE	0.0235	0.0358	0.0158	0.0149
		MAE	0.1137	0.1584	0.0998	0.0990			MAE	0.1137	0.1515	0.0983	0.0961
		$RMSE$	0.1534	0.1979	0.1280	0.1259			$RMSE$	0.1534	0.1891	0.1255	0.1219
	12	MSE	0.0180	0.0291	0.0108	0.0094		12	MSE	0.0180	0.0313	0.0094	0.0090
		MAE	0.1099	0.1399	0.0833	0.0766			MAE	0.1099	0.1515	0.0756	0.0749
		$RMSE$	0.1343	0.1707	0.1040	0.0971			$RMSE$	0.1343	0.1768	0.0969	0.0949
TBL	1	MSE	0.0402	0.0341	0.0318	00268							
		MAE	0.1469	0.1457	0.1362	0.1244							
		$RMSE$	0.2004	0.1847	0.1783	0.1636							
	4	MSE	0.0235	0.0155	0.0159	0.0103							
		MAE	0.1137	0.0914	0.0984	0.0801							
		$RMSE$	0.1534	0.1245	0.1260	0.1015							
	12	MSE	0.0180	0.0127	0.0095	0.0059							
		MAE	0.1099	0.0885	0.0749	0.0608							
		$RMSE$	0.1343	0.1129	0.0973	0.0767							

Table 2.11. Equity Premium Out-of-Sample Forecasting Results for Combining Methods (Quarterly)

Table 2.11 report the equity premium out-of-sample combined forecasting results using the quarterly data. The combination forecasts of Y_{t+1} made at time t are weighted averages of the M individual forecasts based on $\widehat{Y}_{c,t+h} = \sum_{i=1}^{M} \omega_{i,t} \widehat{Y}_{i,t+h}$ where $\{\omega_{i,t}\}_{i=1}^{M}$ are the ex ante combining weights formed at time t, and $\widehat{Y}_{i,t+h}$ is the out-of-sample forecast of the equity premium based on the individual predictive models. The first three methods use simple averaging schemes: mean, median, and trimmed mean. Their discount mean square prediction error ($DMSPE$) combining method employs the following weights: $w_{i,t} = \phi_{i,t}^{-1} / \sum_{j=1}^{M} \phi_{j,t}^{-1}, \phi_{i,t} = \sum_{s=R}^{t-1} \theta^{t-1-s} (Y_{i,t+h} - \widehat{Y}_{i,t+h})^2$ and θ is a discount factor. We consider the two values of 1.0 and 0.9 for θ.

	OS			HMM	LPM	NPM1	NPM2		OS			HMM	LPM	NPM1	NPM2
Mean	1965:1	1	MSE	0.0402	0.0290	0.0312	0.0233	DMSPE	1965:1	1	MSE	0.0402	0.0260	0.0303	0.0223
	−2007:4		MAE	0.1469	0.1411	0.1462	0.1175	$\theta = 1.0$	−2007:4		MAE	0.1469	0.1315	0.1442	0.1174
			$RMSE$	0.2004	0.1703	0.1766	0.1526				$RMSE$	0.2004	0.1611	0.1740	0.1494
		4	MSE	0.0235	0.0250	0.0273	0.0228			4	MSE	0.0235	0.0240	0.0249	0.0214
			MAE	0.1137	0.1283	0.1354	0.1190				MAE	0.1137	0.1248	0.1280	0.1137
			$RMSE$	0.1534	0.1580	0.1652	0.1511				$RMSE$	0.1534	0.1548	0.1578	0.1464
		12	MSE	0.0180	0.0126	0.0139	0.0036			12	MSE	0.0180	0.0079	0.0086	0.0036
			MAE	0.1099	0.1055	0.1115	0.0522				MAE	0.1099	0.0808	0.0840	0.0504
			$RMSE$	0.1343	0.1122	0.1181	0.0601				$RMSE$	0.1343	0.0888	0.0925	0.0596
Median	1965:1	1	MSE	0.0402	0.0254	0.0275	0.0224	DMSPE	1965:1	1	MSE	0.0402	0.0248	0.0260	0.0221
	−2007:4		MAE	0.1469	0.1305	0.1356	0.1178	$\theta = 0.9$	−2007:4		MAE	0.1469	0.1280	0.1306	0.1165
			$RMSE$	0.2004	0.1594	0.1658	0.1497				$RMSE$	0.2004	0.1575	0.1611	0.1487
		4	MSE	0.0235	0.0233	0.0245	0.0208			4	MSE	0.0235	0.0229	0.0239	0.0212
			MAE	0.1137	0.1225	0.1266	0.1115				MAE	0.1137	0.1208	0.1246	0.1126
			$RMSE$	0.1534	0.1527	0.1564	0.1444				$RMSE$	0.1534	0.1513	0.1544	0.1455
		12	MSE	0.0180	0.0080	0.0095	0.0034			12	MSE	0.0180	0.0063	0.0074	0.0036
			MAE	0.1099	0.0819	0.0910	0.0506				MAE	0.1099	0.0715	0.0778	0.0519
			$RMSE$	0.1343	0.0893	0.0977	0.0586				$RMSE$	0.1343	0.0795	0.0860	0.0598
Trimmed	1965:1	1	MSE	0.0402	0.0282	0.0303	0.0224								
Mean	−2007:4		MAE	0.1469	0.1393	0.1442	0.1177								
			$RMSE$	0.2004	0.1680	0.1740	0.1496								
		4	MSE	0.0235	0.0245	0.0259	0.0218								
			MAE	0.1137	0.1269	0.1316	0.1153								
			$RMSE$	0.1534	0.1565	0.1611	0.1477								
		12	MSE	0.0180	0.0111	0.0123	0.0036								
			MAE	0.1099	0.0980	0.1040	0.0517								
			$RMSE$	0.1343	0.1052	0.1108	0.0596								

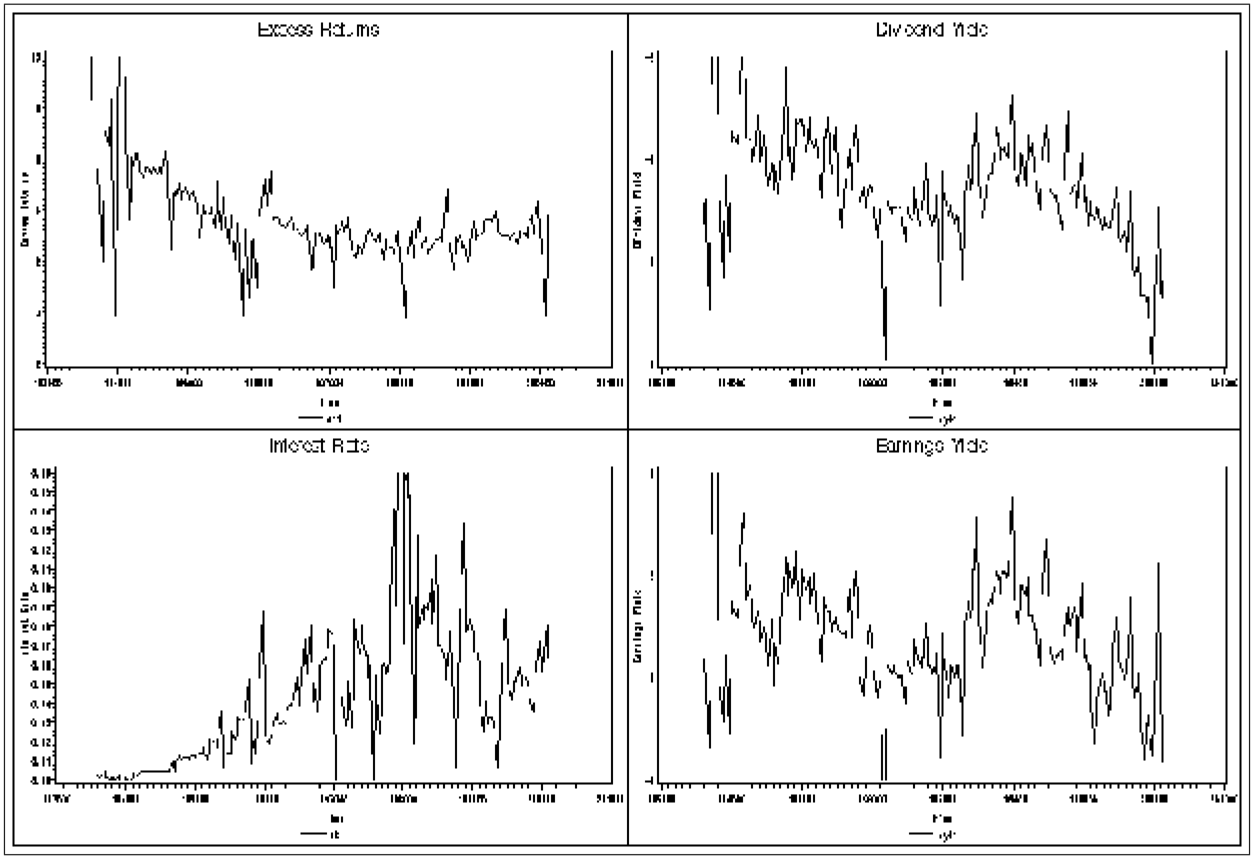


Figure 2.1 US Excess Returns, Interest Rates, Dividend Yield, and Earnings Yield

We plot excess returns, interest rate, dividend yields, and earnings yields from March 1936 to December 2001 quarterly. (March 1936-December 2001 Quarterly)

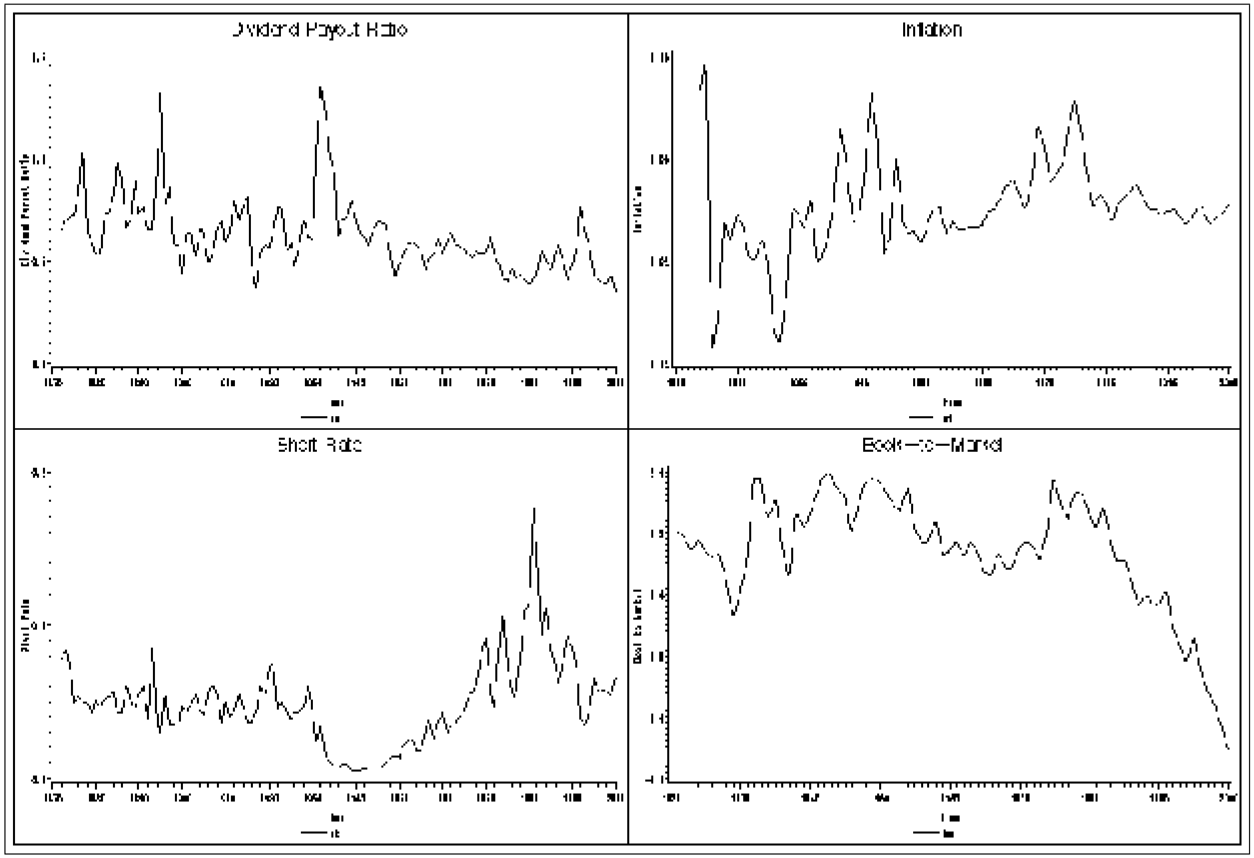


Figure 2.2 US Dividend Payout Raio, Inflation, Short Rate, and Book-to-Market Ratio (Annually)

We plot dividend payout ratio, short rate, inflation, and book-to-market ratio from 1872 to 2005 annually.

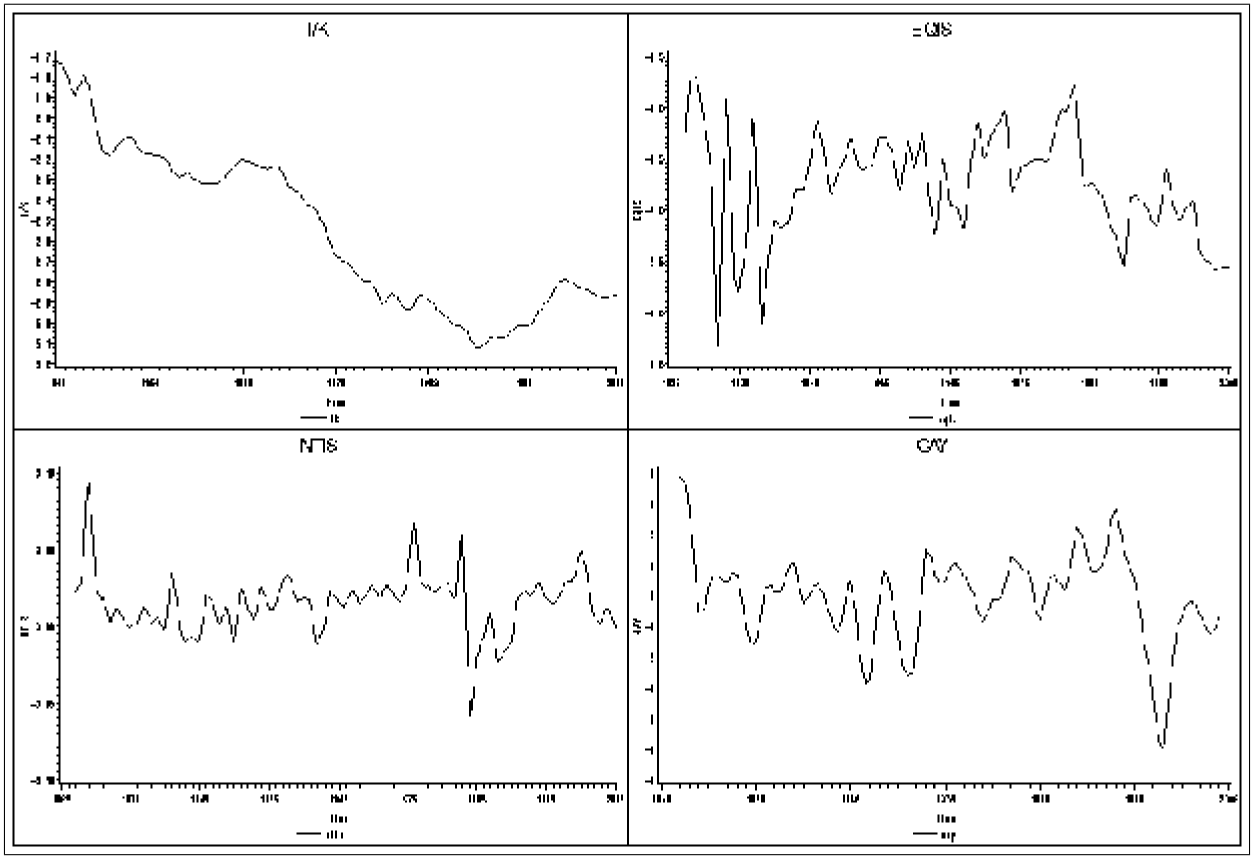


Figure 2.3 US Investment to Capital Raio, Corporate Issuing Activity, and Consumtion Income Ratio (Annually)

We plot investment to capital ratio(i/k), corporate issuing activity (Eqis and Ntis), and consumption, wealth, and income ratio(cay) annually.

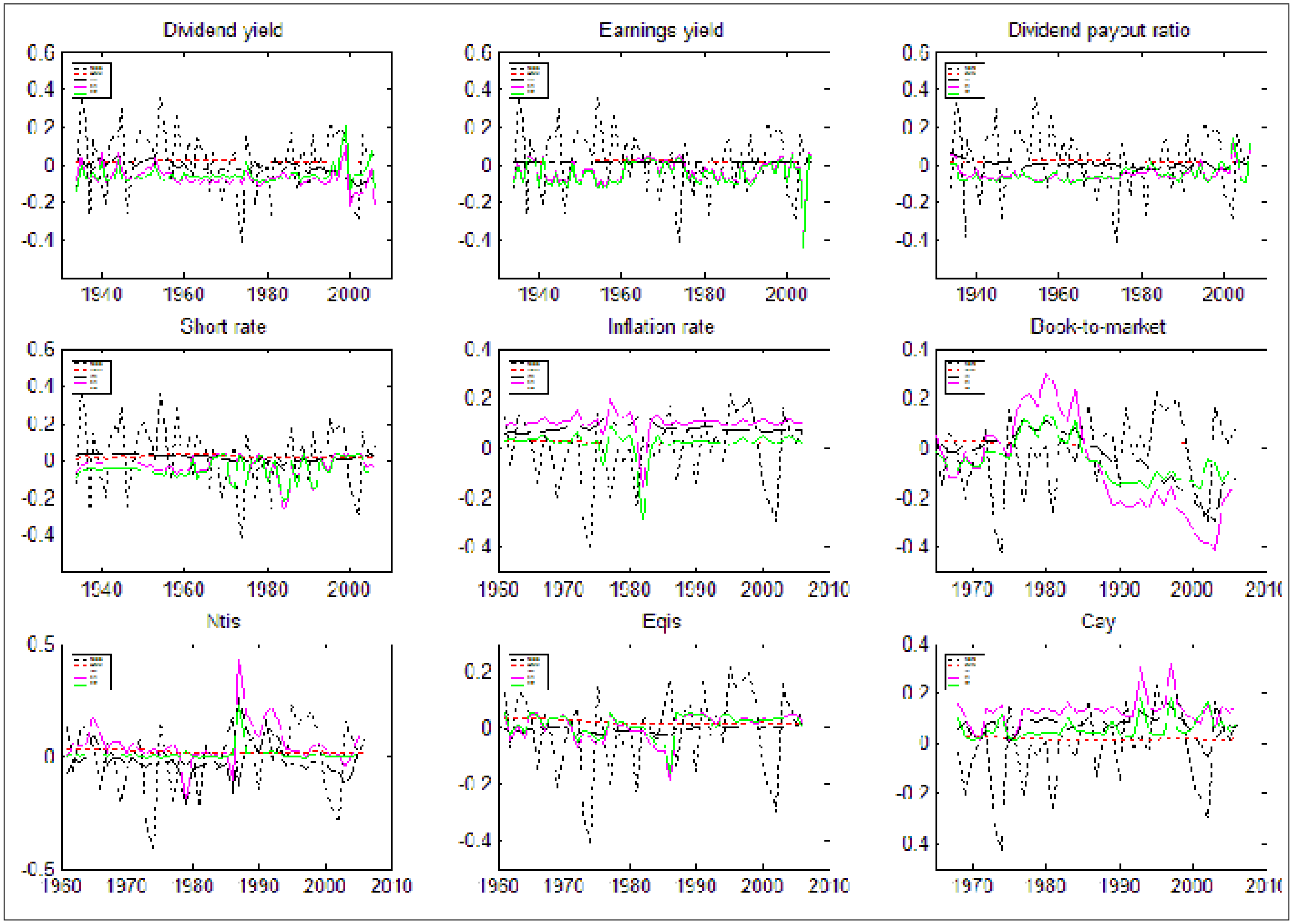


Figure 2.4 Equity Premium Out-of-Sample Forecasting Results for Individual Methods (Annually)

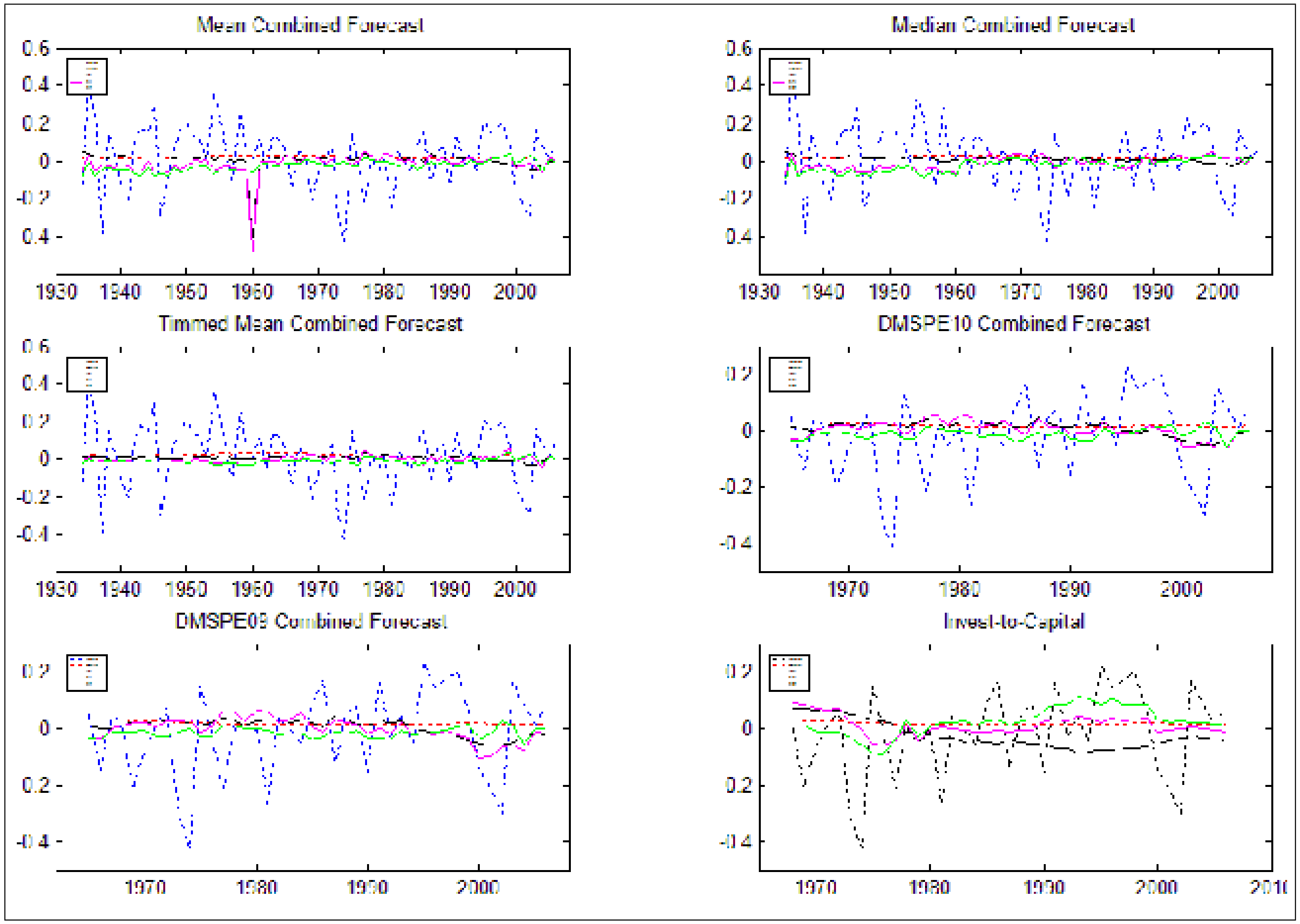


Figure 2.5 Equity Premium Out-of-Sample Forecasting Results for Combined Methods (Annually)

Figure 2.5 illustrate the out-of-sample combined performance for annual predictive regressions for combined methods using annual data.

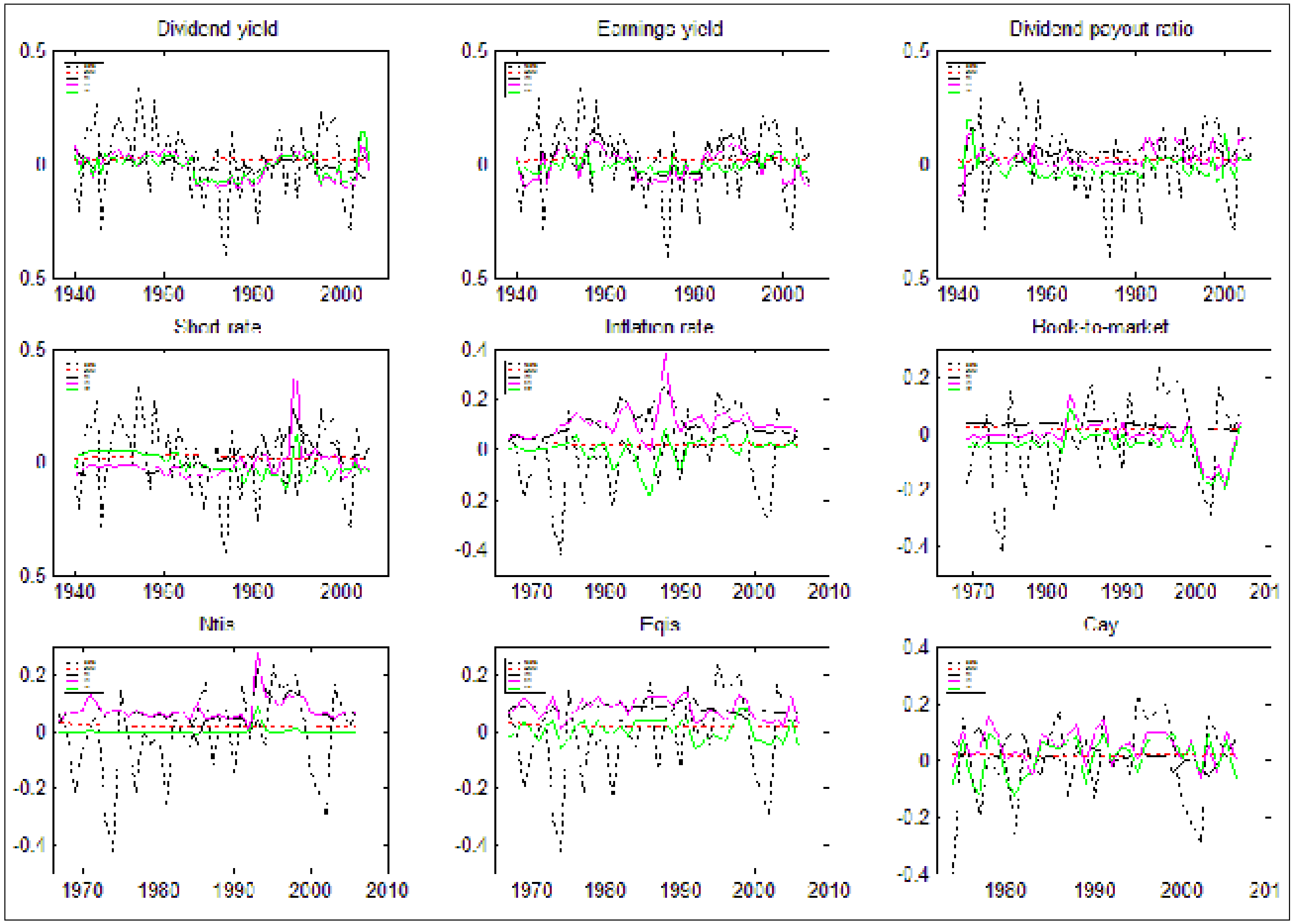


Figure 2.6 Equity Premium Out-of-Sample Forecasting Results for Individual Methods (Annually, 5-year ahead)

Figure 2.6 illustrate the out-of-sample performance for annual predictive regressions for individual methods using annual data over 5-year rolling window.

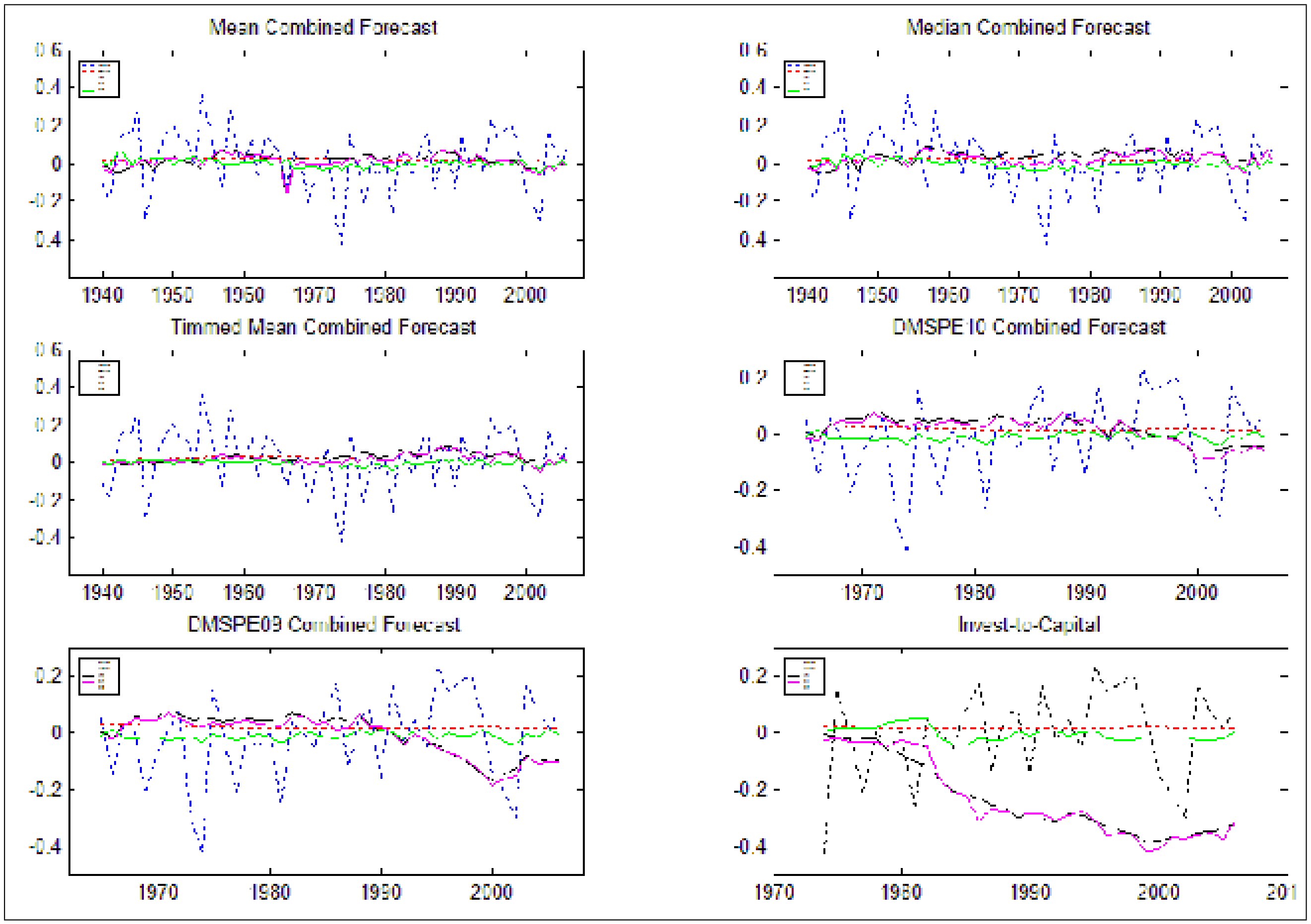


Figure 2.7 Equity Premium Out-of-Sample Forecasting Results for Combined Methods (Annually, 5-year Ahead)

Figure 2.7 illustrate the out-of-sample performance for annual predictive regressions for combined methods using annual data over 5-year rolling window.

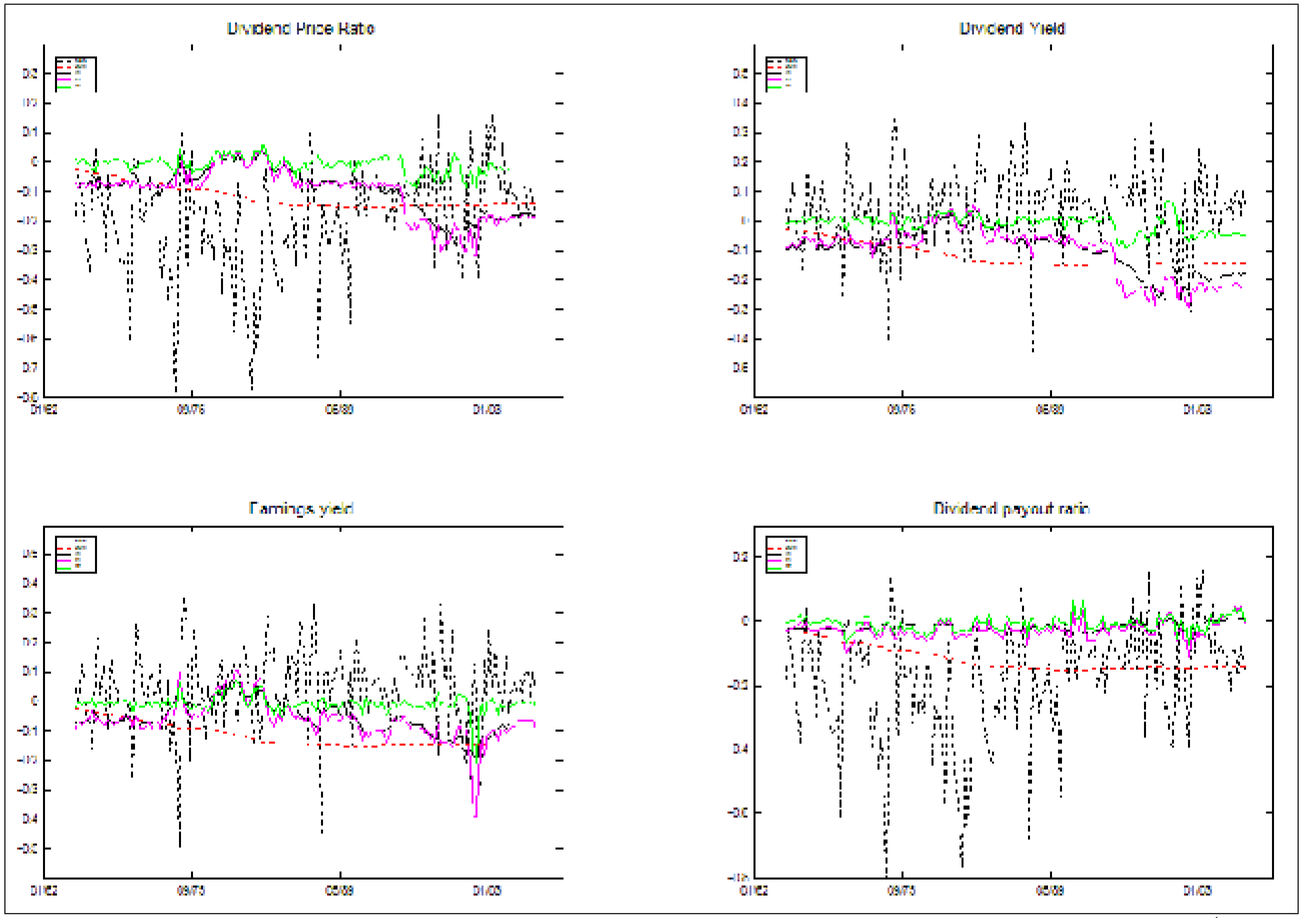


Figure 2.8a Equity Premium Out-of-Sample Forecasting Results for Individual Methods (Quarterly, 1-period ahead)

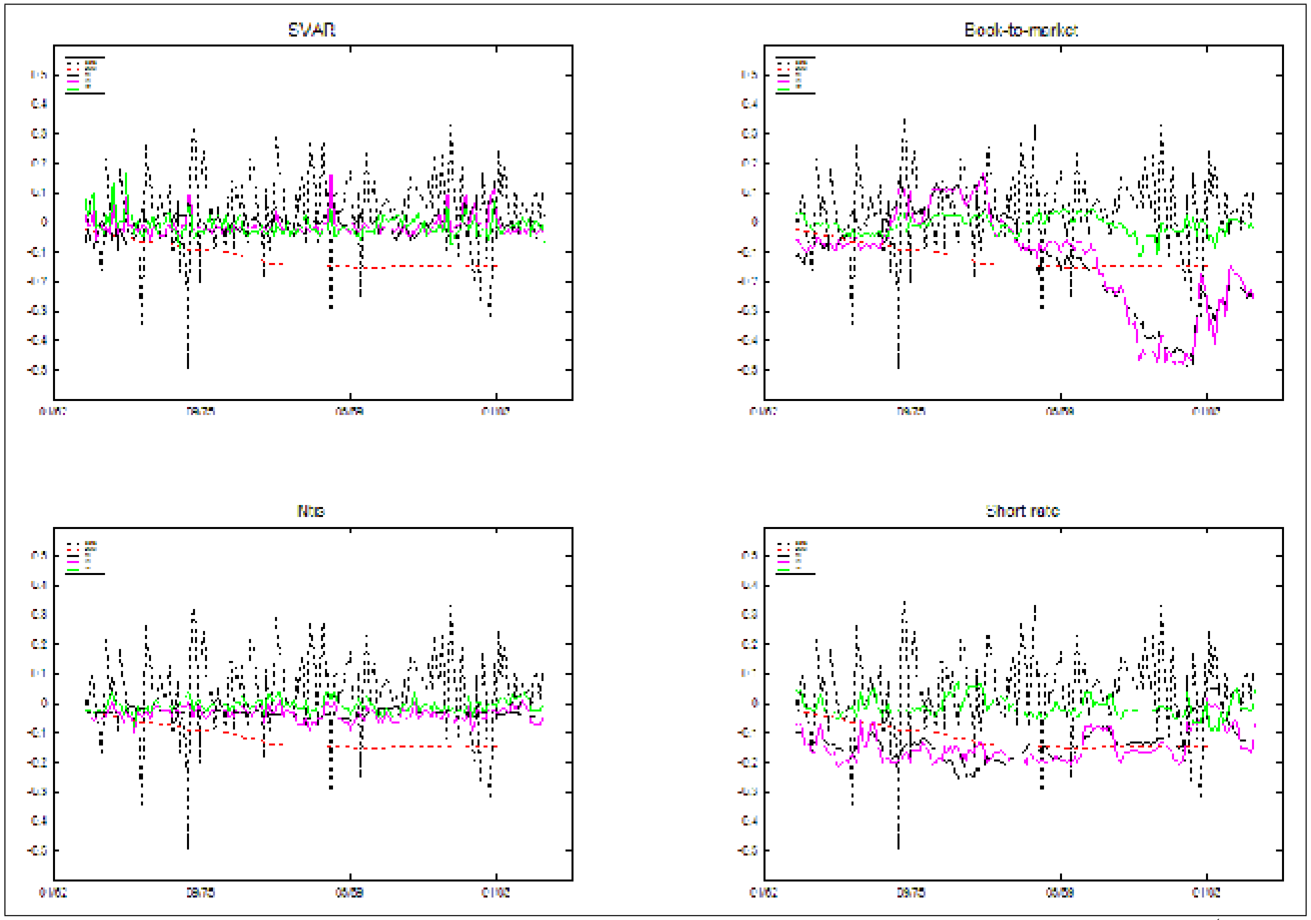


Figure 2.8b Equity Premium Out-of-Sample Forecasting Results for Individual Methods (Quarterly, 1-period ahead)

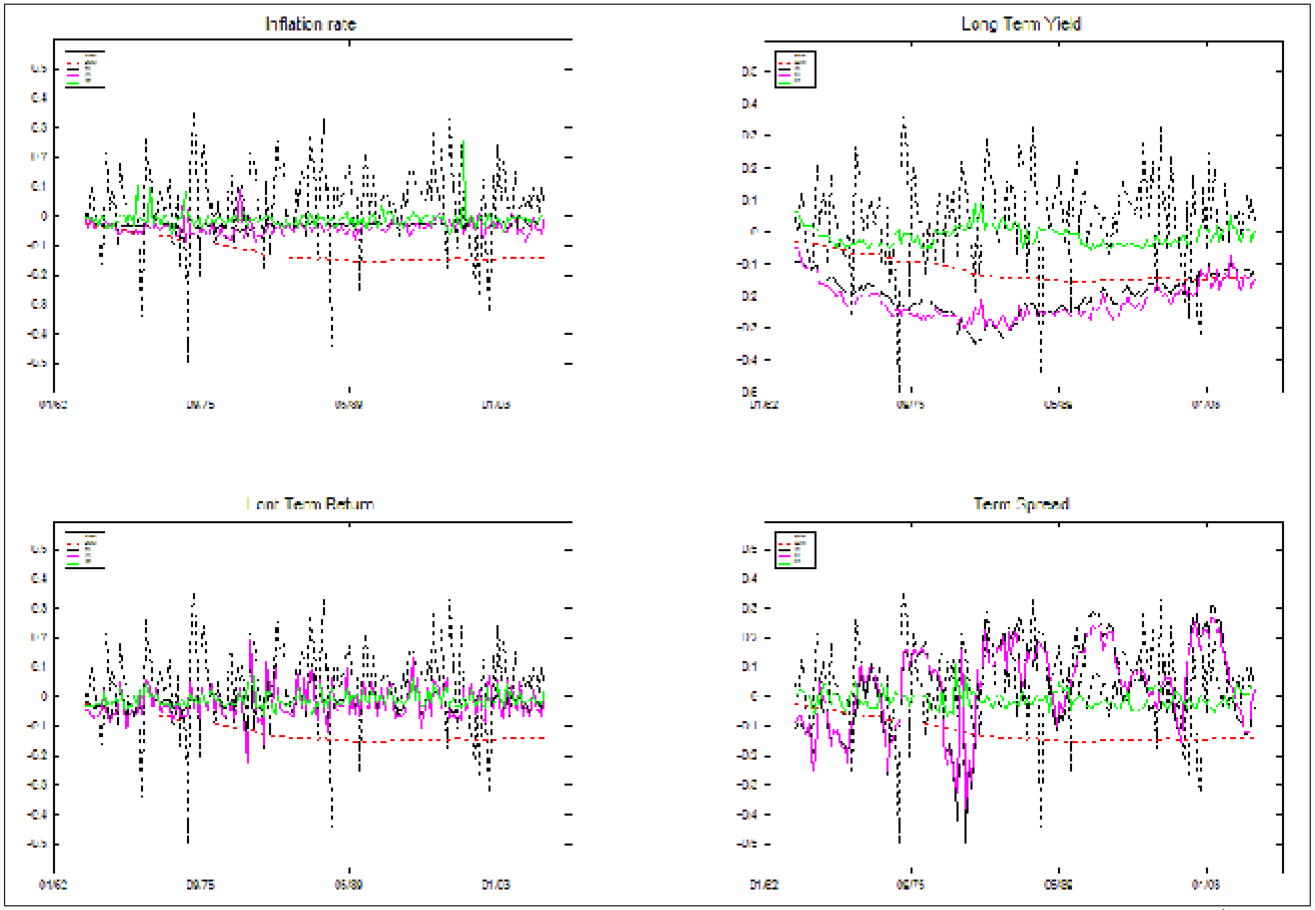


Figure 2.8c Equity Premium Out-of-Sample Forecasting Results for Individual Methods (Quarterly, 1-period ahead)

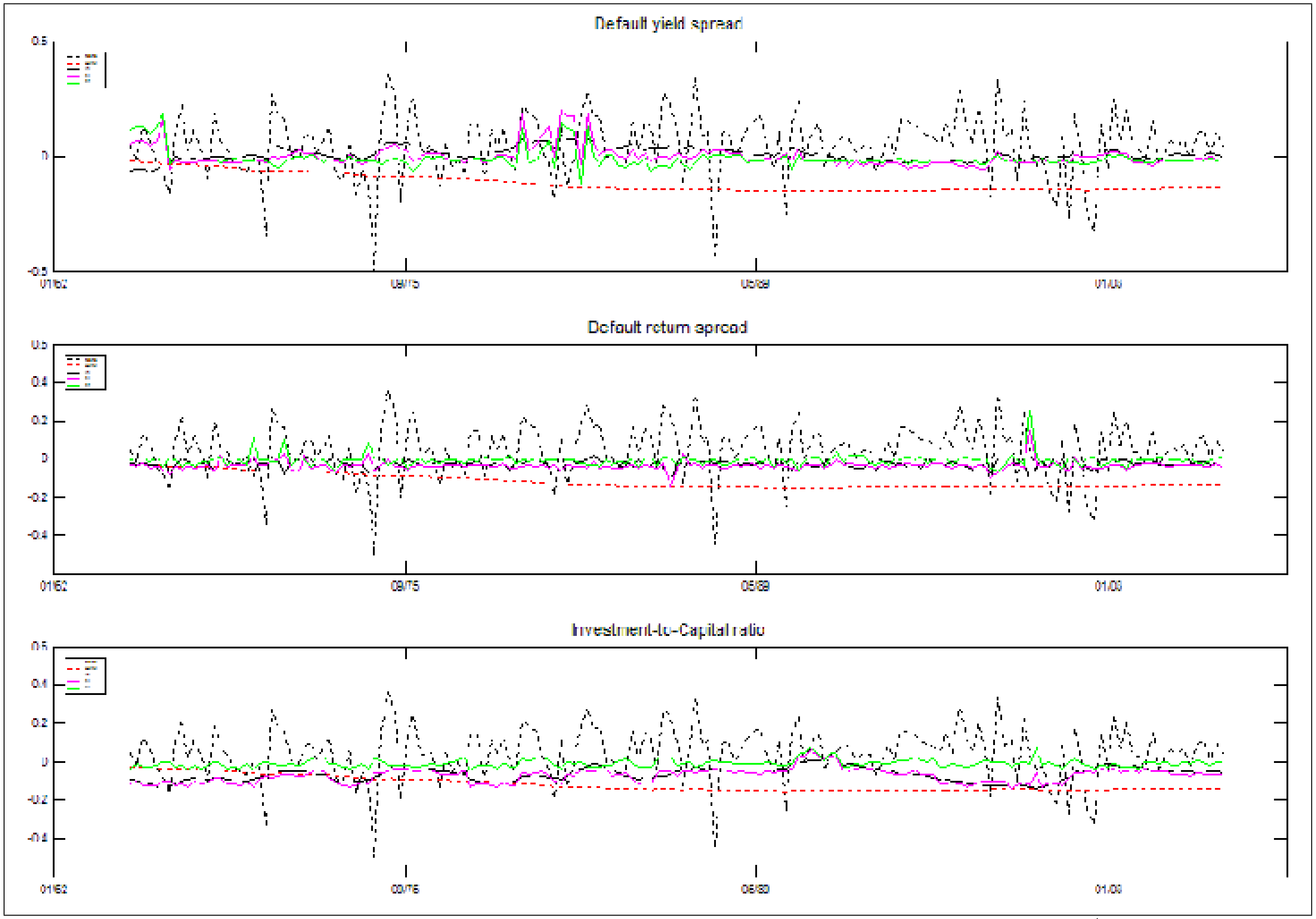


Figure 2.8d Equity Premium Out-of-Sample Forecasting Results for Individual Methods (Quarterly, 1-period ahead)

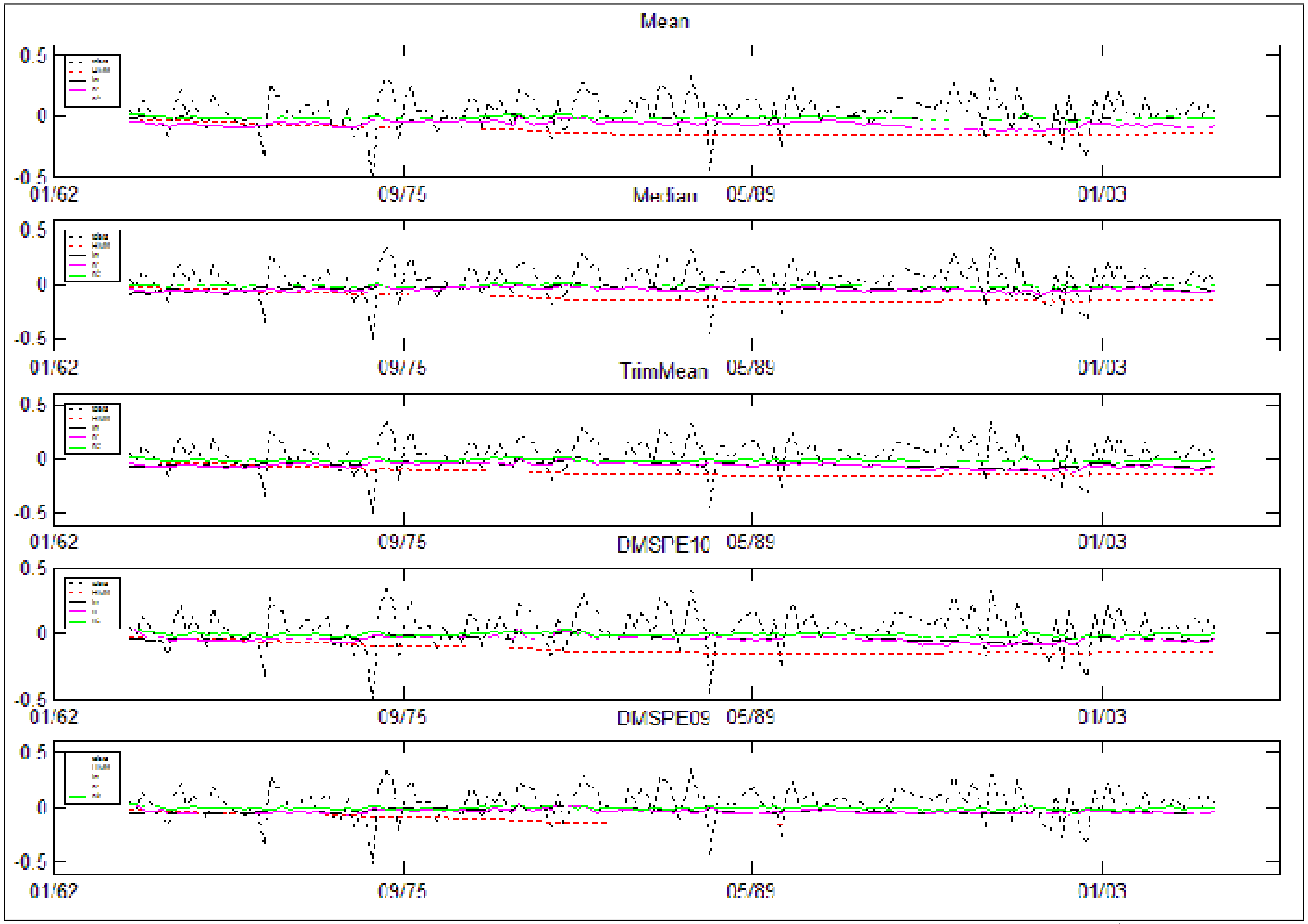


Figure 2.9 Equity Premium Out-of-Sample Forecasting Results for Combined Methods (Quarterly, 1-Period ahead)
Figure 2.9 illustrate the out-of-sample performance for quarterly predictive regressions for combined methods over 1-quarter rolling window.

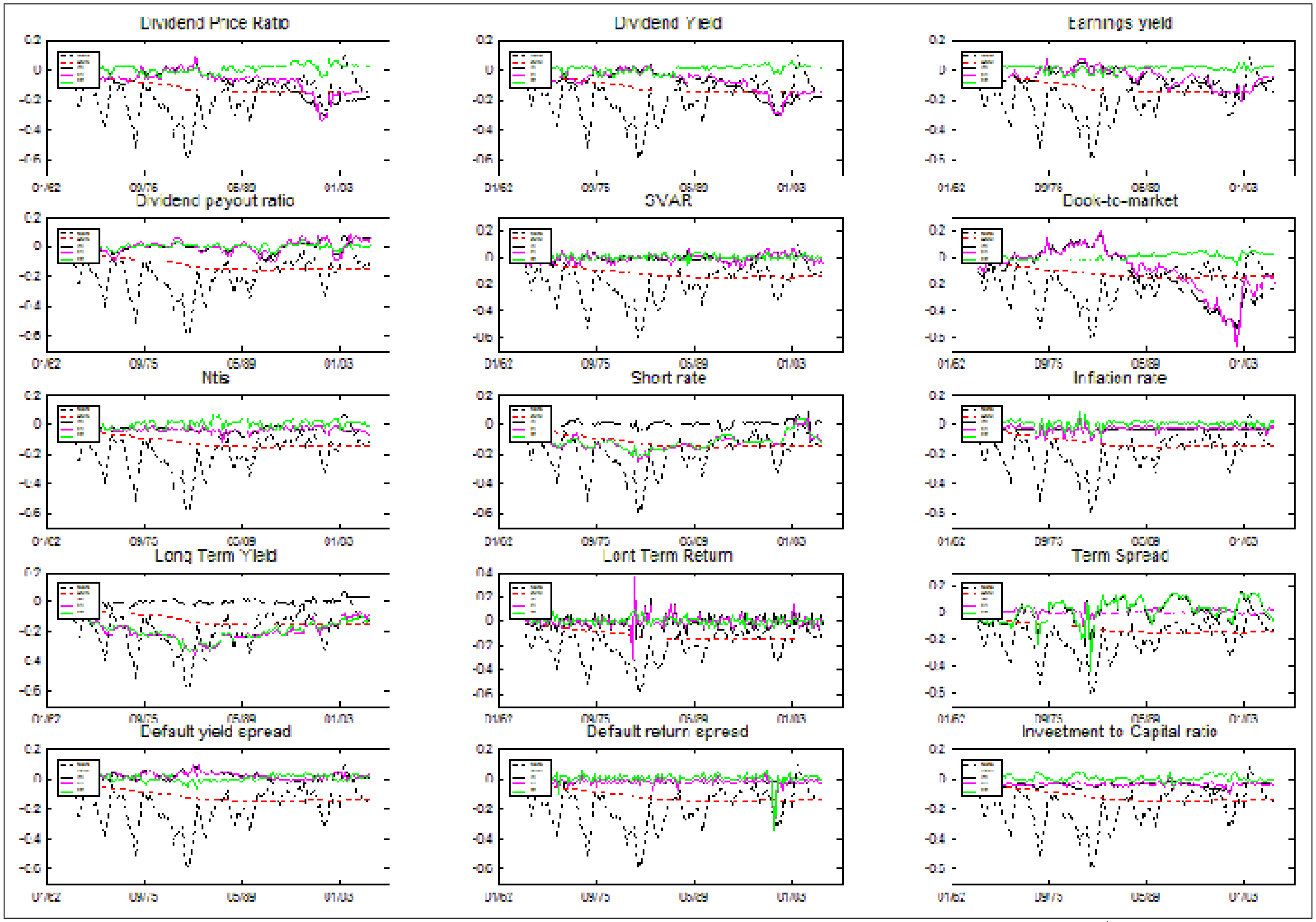


Figure 2.10 Equity Premium Out-of-Sample Forecasting Results for Individual Methods (Quarterly, 4-period ahead)
Figure 2.10 illustrate the out-of-sample performance for quarterly predictive regressions for individual methods over 4-quarter rolling window.

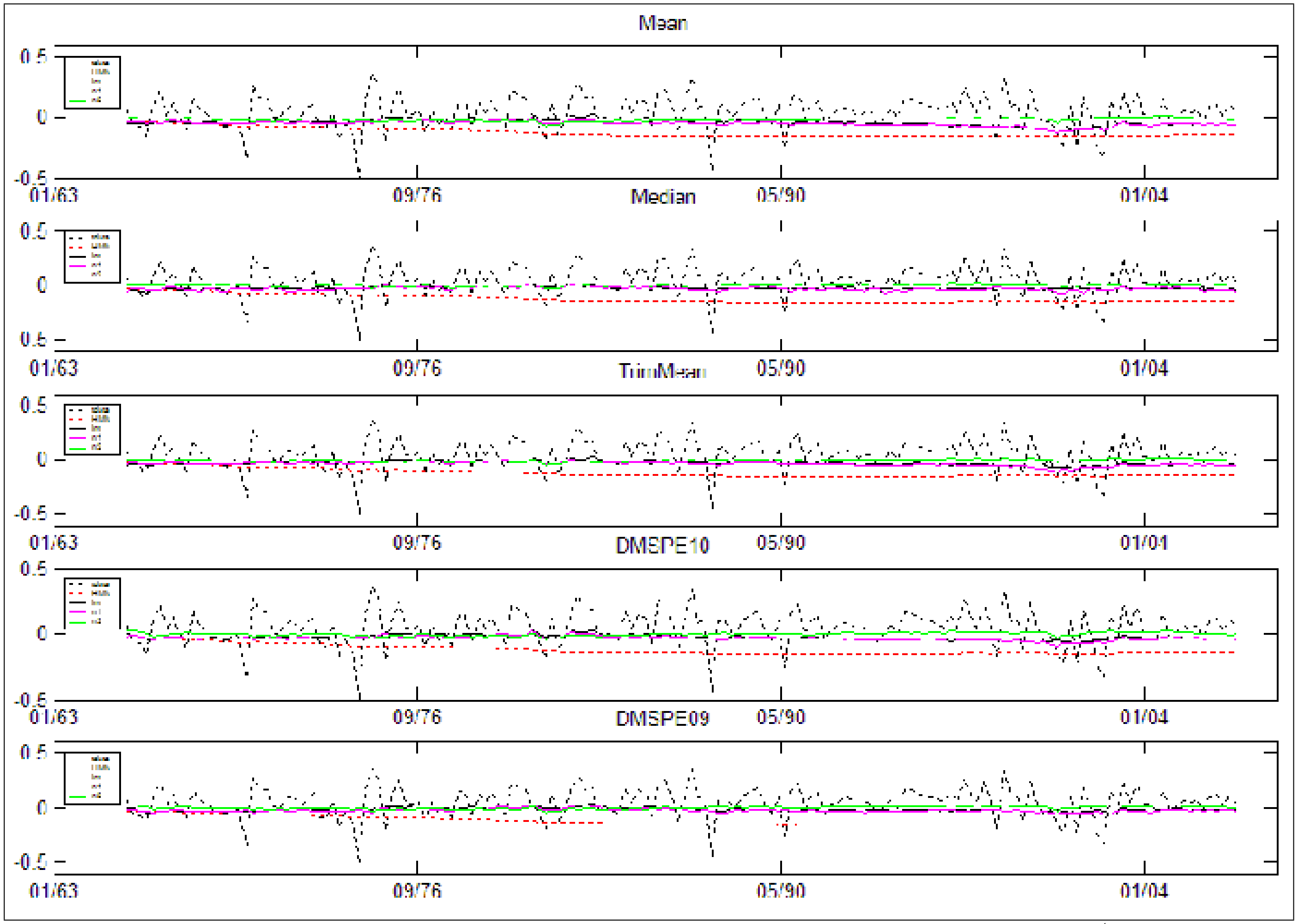


Figure2.11 Equity Premium Out-of-Sample Forecasting Results for Combined Methods(Quarterly,4-Periodahead)
Figure 2.11 illustrate the out-of-sample performance for quarterly predictive regressions for combined methods over 4-quarter rolling window.

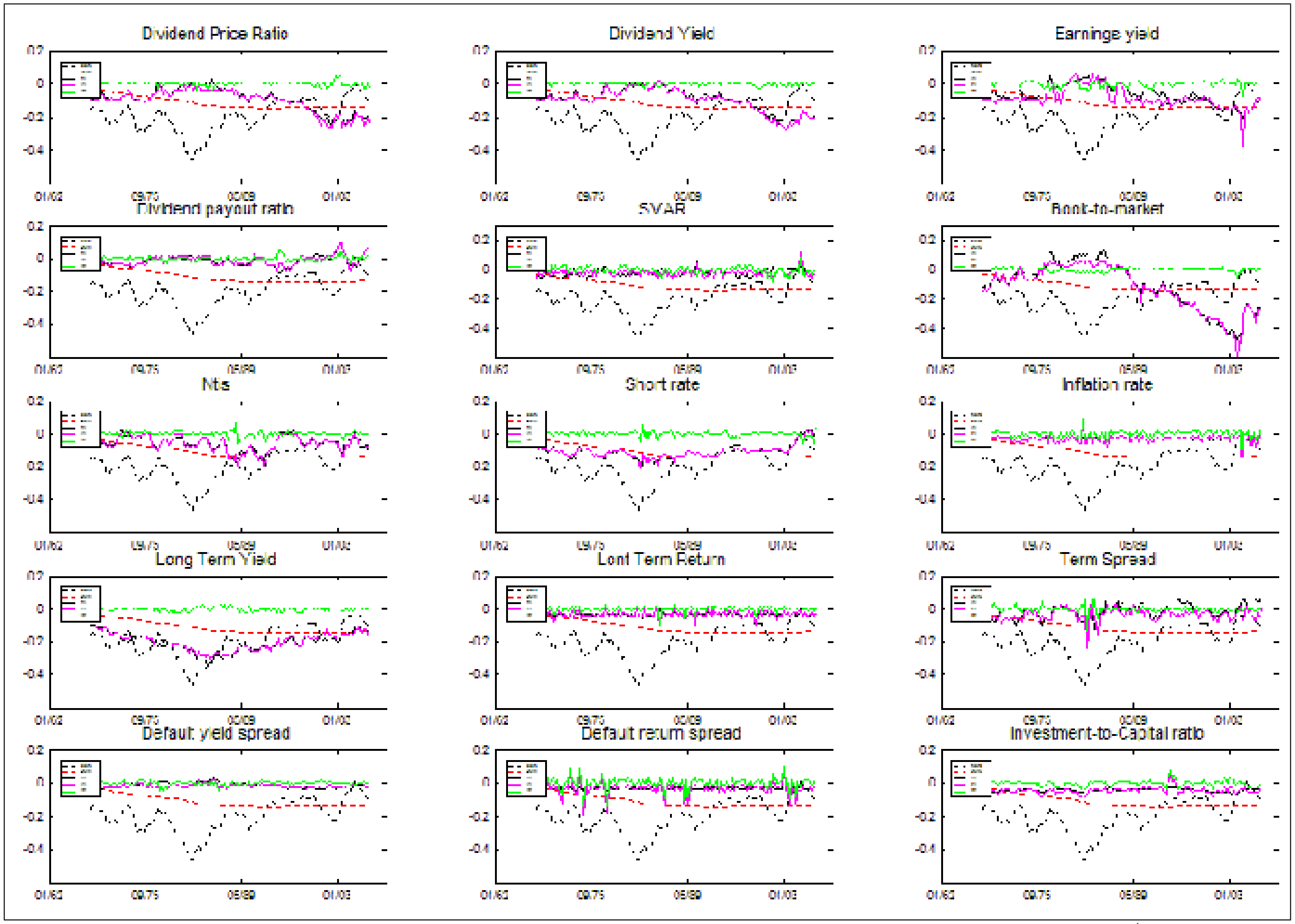


Figure 2.12 Equity Premium Out-of-Sample Forecasting Results for Individual Methods (Quarterly, 12-period ahead)

Figure 2.12 illustrate the out-of-sample performance for quarterly predictive regressions for individual methods over 12-quarter rolling window.

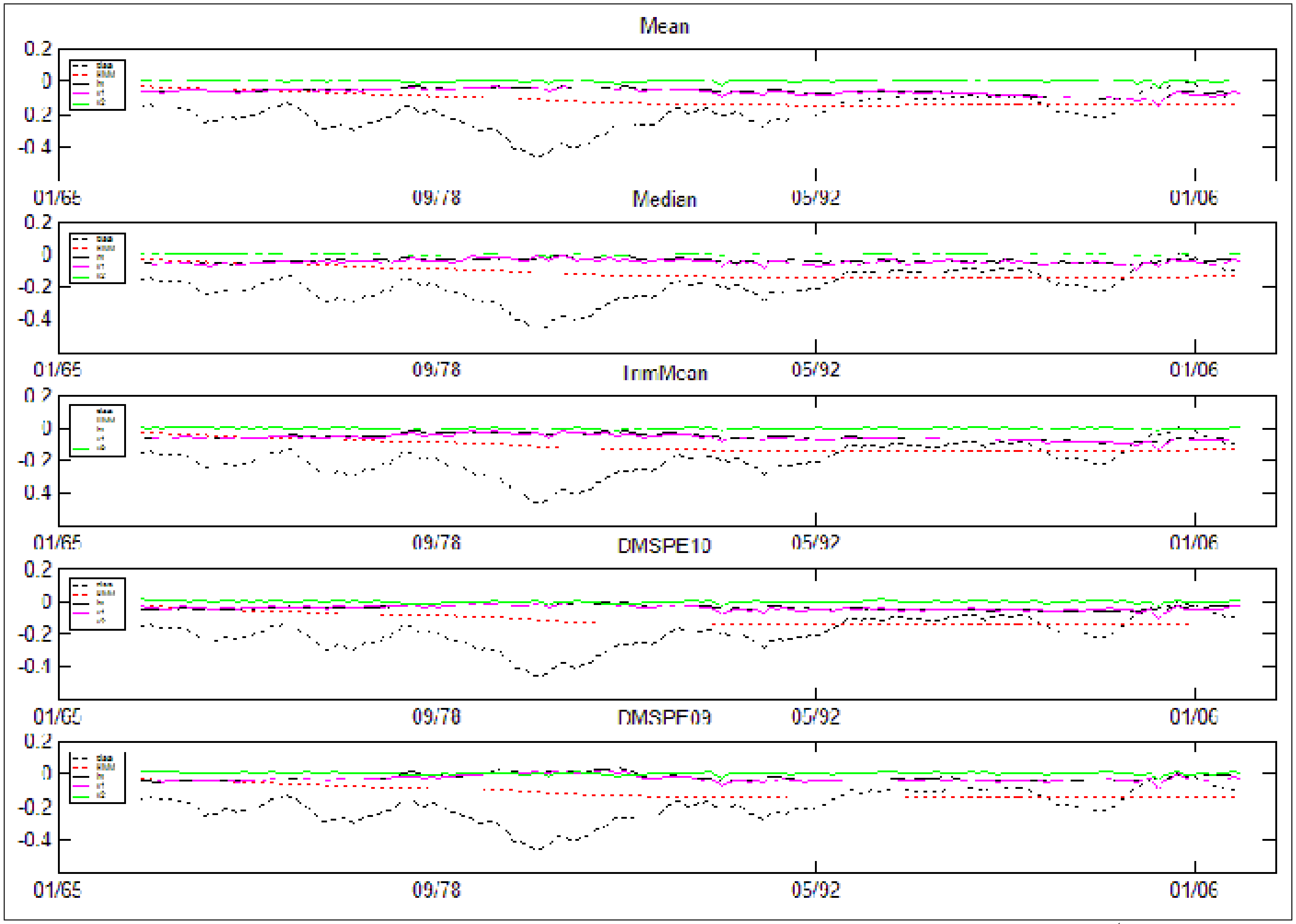


Figure 2.13 Equity Premium Out-of-Sample Forecasting Results for Combined Methods (Quarterly, 12-Period ahead)
Figure 2.13 illustrate the out-of-sample performance for quarterly predictive regressions for combined methods over 12-quarter rolling window.

REFERENCE

[1] Ang, Andrew and Geert Bekaert, 2007, Stock Return Predictability: Is It There?, Review of Financial Studies 20, 651-707.

[2] Andrew Ang, and Jun Liu, 2007, Risk, return, and dividends, Journal of Financial Economics, 85, 1- 38

[3] Baker, M., and J. Wurgler. 2000. The Equity Share in New Issues and Aggregate Stock Returns. Journal of Finance 55:2219–57.

[4] Campbell, J. Y., 1987, Stock returns and the Term Structure, Journal of Financial Economics, 18(2), 373- 399.

[5] Campbell, J. Y., 1991, A Variance Decomposition for Stock Returns, Economic Journal, 101, 157-179

[6] Campbell, J. Y., and R. J. Shiller, 1987, Cointegration and Tests of Present Value Models, Journal of Political Economy, 95, 1067-1087.

[7] Campbell, J. Y., and R. J. Shiller, 1988a, Stock Prices, Earnings, and Expected Dividends, Journal of Finance, 43(3), 661- 676.

[8] Campbell, J. Y., and R. J. Shiller,1988b, The Dividend-Price Ratio and Expectations of Future Dividends and Discount Factors, Review of Financial Studies, 1(3), 195- 227.

[9] Campbell, John Y., and S. Thompson, 2007, Predicting the Equity Premium Out of Sample: Can Anything Beat the Historical Average?, Forthcoming, Review of Financial Studies.

[10] Campbell, J. Y., and M. Yogo, 2006, Efficient Tests of Stock Return Predictability, Journal of Financial Economics, 81(1), 27- 60.

[11] Cavanagh, C. L., G. Elliott and J. H. Stock (1995), Inference in models with nearly integrated regressors. Econometric Theory 11, 1131–1147.

[12] Cochrane, J.H., 1999a, New Facts in Finance, Economic Perspectives 23, 36-58.

[13] Cochrane, J.H., 1999b. Portfolio Advice for a Multifactor World, Economic Perspectives 23, 59-78.

[14] Cochrane, J. H., 1992, Explaining the Variance of Price-Dividend Ratios, Review of Financial Studies, 5, 243- 280.

[15] Cochrane, John H., 2007, Financial Markets and the Real Economy, in John H. Cochrane, ed., Financial Markets and the Real Economy, Volume 18 of the International Library of Critical Writings in Financial Economics, London: Edward Elgar, p. xi-lxix.

[16] Cochrane, J.H., 2008, The Dog That Did Not Bark: A Defense of Return Predictability, Review of Financial Studies, 21, 1533–1575.

[17] Dickey, D., and Fuller, W. , 1979, Distribution of estimators for autoregressive time series with a unit root. Journal of American Statistical Association, 74, 427-31.

[18] Fama, E., 1990, Stock returns, expected returns, and real activity. Journal of Finance, 45 (September), 1089-1108.

[19] Fama, E., and F. French, 1988, Dividend Yields and Expected Stock Returns, Journal of Financial Economics, 22, 3- 26.

[20] Fama, Eugene F. and Kenneth R. French, 1989, Business Conditions and Expected Returns on Stocks and Bonds, Journal of Financial Economics, 25, 23- 49.

[21] Ferson,Wayne E. and Merrick John Jr., 1987, Non-stationarity and stage-of-the-businesscycle effects in consumption-based asset pricing relations, Journal of Financial Economics, 18(1), 127-146.

[22] Ferson, W. E., S. Sarkissian, and T. T. Simin. 2003. Spurious Regressions in Financial Economics? Journal of Finance 58:1393–413.

[23] Froot, K., and M. Obstfeld, 1991, Instrinsic Bubbles: The Case of Stock Prices, American Economic Review, 81, 1189-1217

[24] Foster, F. D., T. Smith, and R. E. Whaley. 1997. Assessing Goodness-of-Fit of Asset Pricing Models: The Distribution of the Maximal R2. Journal of Finance 52:591–607.

[25] Goetzmann, W. N., and P. Jorion, 1993, Testing the Predictive Power of Dividend Yields, Journal of Finance, 48(2), 663- 679.

[26] Goetzmann, W. N., and P. Jorion, 1995, A Longer Look at Dividend Yields, Journal of Business, 68, 483- 508.

[27] Goyal, A., and I.Welch, 2003, The Myth of Predictability: Does the Dividend Yield Forecast the Equity Premium?, Management Science, 49(5), 639- 654.

[28] Goyal, Amit and Ivo Welch, 2007, A Comprehensive Look at the Empirical Performance of Equity Premium Prediction, Forthcoming, Review of Financial Studies.

[29] Hodrick, R. J., 1992, Dividend Yields and Expected Stock Returns: Alternative Procedures for Inference and Measurement, Review of Financial Studies, 5(3), 257- 286.

[30] Hong Y.and Lee T., 2003, Inference on via Genaralized Spectrum and Nonlinear Time Series Models, The Review of Economics and Statistics, November 2003, 85(4), 1048-1062

[31] Kothari, S., and J. Shanken, 1997, Book-to-market, Dividend Yield, and Expected Market Returns: A Time-Series Analysis, Journal of Financial Economics, 44(2), 169- 203.

[32] Lewellen, J., 2004, Predicting Returns with Financial Ratios, Journal of Financial Economics, 74, 209- 235.

[33] Lamont, O., 1998, Earnings and Expected Returns, Journal of Finance, 53(5), 1563- 1587.

[34] Lettau, Martin, and Sydney Ludvigson, 2005, Measuring and Modeling Variation in the Risk-Return Tradeoff, Forthcoming in the Handbook of Financial Econometrics, edited by Yacine Ait-Shalia and Lars-Peter Hansen.

[35] Lettau, M. and S. Van Nieuwerburgh, 2008, Reconciling the Return Predictability Evidence, Review of Financial Studies, 21, 1607–1652.

[36] Nelson, C., and Kim, M., 1993, Predictable stock returns: Reality or statistical illusion?, Journal of Finance , 48(June), 641-61.

[37] Polk, C., S. Thompson, and T. Vuolteenaho. 2006. Cross-Sectional Forecasts of the Equity Premium. Journal of Financial Economics 81:101–41.

[38] Ponti , J., and L. D. Schall, 1998, Book-to-Market Ratios as Predictors of Market Returns, Journal of Financial Economics, 49(2), 141-160.

[39] Rapach, D. E., and M. E. Wohar, 2006, In-Sample vs. Out-of-Sample Tests of Stock Return Predictability in the Context of Data Mining, Journal of Empirical Finance, 13(2), 231–247.

[40] Rapach, Strauss, and Zhou, 2009, Out-of-Sample Equity Premium Prediction: Combination Forecasts and Links to the Real Economy, working paper

[41] Rozeff, M. ,1984, Dividend yields are equity risk premiums. Journal of Portfolio Management, 11 (Fall), 68-75.

[42] Stambaugh, R. ,1986, Biases in regressions with lagged stochastic regressors. Working Paper no. 156. Chicago: University of Chicago, Graduate School of Business.

[43] Stambaugh, R. F., 1999, Predictive Regressions, Journal of Financial Economics, 54, 375- 421.

[44] Stock, J.H. and M.W. Watson, 1999, Forecasting Inflation, Journal of Monetary Economics, 44, 293–335.

[45] Stock, J.H. and M.W.Watson, 2003, Forecasting Output and Inflation: The Role of Asset Prices, Journal of Economic Literature, 41, 788–829.

[46] Stock, J.H. and M.W.Watson, 2004, Combination Forecasts of Output Growth in a Seven-Country Data Set, Journal of Forecasting, 23, 405–430.

[47] Stock, J.H. and M.W.Watson, 2006, Forecasting with Many Predictors, In G. Elliott, C.W.J. Granger, and A. Timmermann (Eds.), Handbook of Economic Forecasting, Amsterdam: Elsevier, pp. 515–554.

[48] Torous, W., and R. Valkanov, 2000, Boundaries of Predictability: Noisy Predictive Regressions, Working Paper, UCLA.

[49] Valkanov, R., 2003, Long-Horizon Regressions: Theoretical Results and Applications, Journal of Financial Economics, 68(2), 201- 232.

[50] West, K., 1988, Dividend Innovations and Stock Price Volatility, Econometrica, 56, 37-61

[51] Wolf, M., 2000, Stock Returns And Dividend Yields Revisited: A New Way To Look At An Old Problem, Journal of Business and Economic Statistics, 18(1), 18- 30.

Chapter 3
An Intraday Analysis of Related Investment Vehicles Traded in the NYSE and AMEX

3.1 INTRODUCTION

The questions money managers are interested in are (1) what are the trading pattern of different securities? (2) what are the best trading strategies to manage a portfolio or basket in order to maximize profits and minimize risks? There is a vast amount of literature on how investors trade. DeLong, Shleifer, Summers, and Waldmann (1990) show that passive traders and rational speculators trade on firm fundamentals and/or superior information, while positive-feedback traders simply buy when prices rise and sell when prices fall. Hong and Stein (1999) show that momentum traders can make profit by implementing simple strategies such as trendchasing. A number of large and presumably sophisticated money managers use momentum approaches. Diversification into global equity markets is one of the approaches for money managers to improve the risk/return trade-off of a stock portfolio. There are three similar trading vehicles: American depositary receipts (ADR), exchange-traded funds (ETF), and closed-end funds (CEF), which specialize in holding a portfolio of foreign equities of one country or a group of countries in a region on US stock exchanges. The purpose of this paper is to investigate what kind of trading strategies investors pick up if they choose to invest in ADR, ETF, and CEF across countries. If the trading behaviors of ADR, ETF, and CEF from one country are different from each other, does one type of security have imformation advantage over the other? If the trading activities relate to past returns, do they follow positive feedback trading strategies? Investigating those questions is important not only for us to understand the determinants of trading volume, liquidity, and stock returns but also for money managers and policymakers to devise efficient trading strategies and improve the liquidity and efficiency of financial markets.

In order to investigate the trading behaviours of the three securities, I focus on how the trading activities differ, in real time, among ADR, ETF, and CEF. First, this paper examines whether ADR, ETF, and CEF trade at different transaction prices across countries. It helps me to understand whether one type of security have an advantage of trading over the other. Second, I use the VAR model to estimate the correlations of return, volume, liquidity and volatility among the three types of securites. It shows the relative relation of trading among the three securities. Third, I examine the short-horizon dynamic relation between the order imbalance and both past and subsequent returns by type of securities using high-frequency intraday data. The dataset with a special construction contains ADR, ETF, and CEF of 29 countries and 4 regions mostly from March 18th, 1996 to Jan. 5th, 2007.

Previous research mostly focuses on whether different clienteles of investors (foreign v.s. domestic) have advantage of information or trading one over the other. Choe, Kho, and Stulz (2005), and Hau (2001a) find that foreigners are at a disadvantage using Korean and German data respectively. Seasholes (2000), Grinblatt and Keloharju (2000), and Froot and Ramadorai (2001) show that foreigners do better than local investors using Taiwanese, Finnish, and a cross section of 25 countries data. Now I am focusing not on different types of investors but on securities. This paper first examines how the buying v.s. selling activities differ among the three types of securites, ADR, ETF, and CEF. For each country (region), I choose the ADR with the most heavily traded and highest turnover as the leading ADR of that country (region) by CRSP data. I compute the relative price ratio[22] for thethree securities in 5 minute interval in the sample. First, I find that the investors are at a disadvantage investing in ADR relative to ETF (CEF) on average. The average disadvantage of investing in leading ADR relative to ETF (CEF) is of the order of 11 (10) basis points for purchases and 12 (13) basis points for sales. This means that on a roundtrip trade the investors investing in leading ADR face greater transaction costs of the order of 23 basis points than investors investing in ETF (CEF). Second, there is no significant evidence to show whether the investors are at a disadvantage investing in ETF relative to CEF on average. From the results above, I can infer that ETF and CEF have advantages of trading over leading ADR. I can also infer that institution investors trade at a disvantageous price compared to individual investors on average. Those results might come from the difference of leading ADR, ETF, and CEF. Without the dataset of the exact information about the buys and sells, my approach has some limitation when using the classification of buys and sells by Lee and Ready (1991).

I use the VAR model to estimate the relation of return, quoted spread, volume and volatility among the three types of securites. I find that the returns of one security are positively related to the past returns of the other two securities. For example, on average, the returns of leading ADR are 2.6% related to the past returns of ETF and 2.7% related to the past returns of CEF. On average, the volatilities and liquidities (measured by quoted spreads) of one security is also positively related to the past volatilities and liquidities of the other two. The results verify our hypothesis that the trading behaviours of leading ADR, ETF, and CEF are correlated and we can forecast the future returns of one security by the past returns of the other two.

[22] It follows the definition of Choe, Kho, and Stulz (2005) and Bailey, Mao and Sirodom (2006).

A number of earlier papers have examined the relation between past returns and trading activity. They mainly address the relation between the net trading and returns among different types of investors institution, individual, and foreign investors. Griffin, Nardari, and Stulz (2002) point out that a model with perfect information cannot explain one of the stylized facts in international finance: the positive contemporaneous relationship between net equity flows and returns. They argue that a model in which foreign investors are less informed than domestic investors can explain this stylized fact. Brennan and Cao (1997) show positive feedback trading results in that rational U.S. investors lack information about foreign securities and condition their trades on the recent return performance of individual foreign securities or national stock indexes. Bohn and Tesar (1996) and Clark and Berko (1996) show a positive contemporaneous relation between equity flows and stock returns using monthly data. Froot, O'Connell, and Scasholcs (1998) investigate the relation between equity flows and stock index returns with trades of 44 countries using State Street Bank& Trust database, and find strong evidence that flows into a market are positively correlated with lagged returns in that market.

In this paper, I investigate dynamic relation between the concurrent and past order flow-return relation of the three securities. I want to further check the trading behavior among the three securities, and two methodolgies are applied. One methodology I use is to investigate the cumulative returns around the largest and smallest buying and selling activity of leading ADR, ETF, and CEF. I find that the investors buy when returns and prices increase and sell when returns and prices decrease. The cumulative returns of CEF around the sell trades are higher than those of leading ADR and ETF. The other methodology I use is to use the

VAR model and investigate the relation between the net trading and returns among leading ADR, ETF, and CEF across the countries. The results of VAR model tell us that the trading of the three securities are positively correlated and the buy and sell trades of one security are decided not only by the net order imbalances and past returns of the certain security itself but also by the net order imbalances and past returns of the other two securities. Furthermore, the past net order imbalances and past returns of the three securities can do a good job in predicting the future returns of leading ADR, ETF, and CEF.

How can I interpret trading on leading ADR, ETF, and CEF? It may be due to the liquidity, information or behaviour reasons. Admati and Pfleiderer (1988) show that informed investors seek to execute their trades at times when the market is liquid and active to minimize market impact and to prevent other market participants inferring their information. I investigate the average quoted spreads and depths around the largest and smallest buying and selling activity of leading ADR, ETF, and CEF. I do not find persuasive evidence on the liquidity reasons to explain the trading behaviour of leading ADR, ETF, and CEF.

I want to examine how the trading of the three securities are related to market information and whether the profitability and contribution to price discovery of the trading are consistent with informed trading. Returns and order flow could move together in response to new information that is relevant for valuation. Brennan and Cao (1996) show mutual fund investors are relatively uninformed about the distribution of returns on the risky asset. Thus, after news is released, mutual fund investors are net buyers (sellers) in response to public release of good (bad) news. Although the model does not explicitly predict that flow will lag returns, Brennan (1998) argues that a lag of one or several days is consistent with information driving returns and flow, if some investors do not stay attuned to the latest news. Empirical work on international return behavior suggests that foreign stocks respond contemporaneously or with a lag to common news that they share[23]. Griffin, Harris, and Topaloglu (2003) and Bailey, Mao and Sirodom (2006) use the regression of the net order imbalances on lag net order imbalances and lag returns to explore the relation between the trading and infomation.

My hypothesis is that the trading behaviour of the three securities might come from the correlated information set. The results of VAR model tell us that the trading of the three securities are correlated and the buy and sell trades of one security are not only decided by the net order imbalances and past returns of the certain security itself but also the net order imbalances and past returns of the other two securities. It implies that the trading on the three securities leading ADR, ETF, and CEF, selected from the same country, belong to the same information set.

This paper is also highly related to positive feedback trading. Dornbusch and Park (1995) contend that the trades of foreign investors are affected by past returns, so that they buy when prices have increased and sell when they have fallen. Such a practice is called positive feedback trading. Choe, Kho, and Stulz (1999) find strong evidence of positive feedback trading and herding by foreign investors before the period of Korea's economic crisis. Froot, O'Connell, and Scasholcs (1998) suggest that the positive feedback ttading may be evidence that some foreign investors use returns to extract information about future returns. Richards (2005) show positive feedback trading with respect to global, as well as domestic, equity returns using the dataset that contain the aggregate daily trading of all foreign

[23] There are related literature on trading across markets and information. See Eun and Shim (1989), Hamao, Masulis, and Ng (1990), Craig, Dravid, and Richardson (1995), Karolyi and Stulz (1996).

investors in six Asian emerging equity markets. The results show that investors buy one security when price increases and sell when price decreases. So the trading of leading ADR, ETF, and CEF follows the positive feedback trading. If the increasing returns are observed, the buy trades of one security take place. If the decreasing returns are observed, the sell trades of one security take place. This indicates that investors tend to be momentum traders, and they use returns information from the trading of the three securities to guide the direction of their trading.

Finally, this paper also sheds light on the impact of trading on market efficiency. Lakonishok, Shleifer, and Vishny (1992) claim that positive-feedback trading and herding have potential to destabilize stock prices; however, they find little supporting evidence in their pension fund sample. Wermers (1999) finds that mutual fund herding stabilizes stock price by speeding up the price adjustment process. One might conjecture that increased trading can make stocks more volatile or riskier. The higher returns following an increase in net order imbalances may simply be compensated for the increased risk. I investigate the average return volatilities around the largest and smallest buying and selling activity of leading ADR, ETF, and CEF. The increase in volatilities observed is too small and too temporary to explain the trading and returns I observe. So the evidence of empirical results could not reject the hypothesis that positive-feedback trading improves market efficiency.

There are two contributions of this paper to the literature: (1) This is the first paper that investigates the trading behaviors of three related securities, specifically ADR, ETF, and CEF. ETFs are desirable investment vehicles for both institutional and private investors. It helps investors and money managers to conduct efficient trading strategies. (2) This paper empirically verifies that the trading behaviors of ADR, ETF, and CEF follow positive feedback trading and are consistent with the theoretical models by DeLong, Shleifer, Summers, and Waldmann (1990) and Hong and Stein (1999).

The balance of this paper is organized as follows. Section 2 discusses the dataset and sample construction. Section 3 investigates whether the Leading ADR, ETF, and CEF trade differently and correlatedly. Section 4 analyze the dynamic relation between net individual trading and short horizon returns. Section 5 give some explanations. Section 6 is a summary and conclusion.

3.2 DATA AND SAMPLE CONSTRUCTION

3.2.1 The Three Vehicles: ADR, ETF, and CEF

In this paper I investigate three types of securities that allow the investors to access the international markets, ETF, ADR and CEF. We take ETF as the "base" security in this paper. ETFs are bundles of foreign stocks that trade on the AMEX/NYSE and are priced in US dollars. ETFs are desirable investment vehicles for both institutional and private investors. ETFs are more accessible and more convenient trading vehicles for smaller orders or orders motivated by liquidity needs. The presence of liquidity traders may attract informed traders to take advantage of potential profit opportunities in the ETF market. They combine characteristics of individual stocks and traditional index funds. They are designed to be a low cost instrument that tracks a foreign stock index and can be traded intraday like regular stocks with stops, limits, short sales, etc. ETFs can achieve a desired portfolio position with one transaction, saving the costs of multiple trades in individual stocks. Because international ETFs are traded in U.S. markets, and subject to the same trading rules and practices, they also avoid some of the typical problems of international stock investments such as illiquidity, changing exchange rates, and trading restrictions. Using ETFs ensures that the analysis is unaffected by the differences in market clientele, transparency, and other aspects of market structure.

Closed end funds (CEF) are typically traded on the major stock exchanges in US, such as NYSE and AMEX. New shares are rarely issued after the fund is launched; Shares are not normally redeemable for cash or securities until the fund liquidates. Typically an investor can acquire shares in a closed-end fund by buying shares on a secondary market from a broker, market maker, or other investor, as opposed to an open-end fund where all transactions eventually involve the fund company creating new shares on the fly (in exchange for either cash or securities) or redeeming shares (for cash or securities). Like their better-known open-ended cousins, closed-end funds are usually sponsored by a funds management company which will control how the money is invested. They begin by soliciting money from investors in an initial offering, which may be public or limited. The investors are given shares corresponding to their initial investment. The price of a share in a closed-end fund is determined partially by the value of the investments in the fund, and partially by the premium (or discount) placed on it by the market. Closed-end funds offer a fixed supply of shares, and as demand changes they frequently trade at appreciable discounts from (and sometimes premiums to) their net asset values (NAVs).

Closed-end funds trade on exchanges and in that respect they are like exchange-traded funds (ETFs)[24], but there are important difference between these two types

[24]ETFs are open-ended in the sense that units of the ETF shares can be swapped for pre-announced portfolios of the underlying assets and a small cash component representing accumulated dividends at the end of each trading day. As the supply of the ETF can be altered at any time, arbitrage ensures that its price closely tracks the index. Managers of the ETFs may buy either all the stocks in the index or a sample of stocks to track the index.

of securities. The price of a closed-end fund is completely determined by the valuation of the market, and this price often diverges substantially from the NAV of the fund assets. In contrast, the market price of an ETF trades in a very close range of its net asset value, because the structure of the ETF would allow major market participants to gain arbitrage profits if the market price of the ETF were to diverge substantially from the NAV. The market prices of closed-end funds are often ten to twenty percent different than the NAV while the value of an ETF would only very rarely differ from the NAV by more than one-fifth of a percent.

An American Depositary Receipt (ADR) represents ownership in the shares of a foreign company trading on US financial markets. ADRs[25] are commonly traded on all major stock exchanges (NYSE, AMEX, and NASDAQ) or Over-the-Counter (OTC) market in US dollars. ADRs enable US investors to buy shares in foreign companies without undertaking cross-border transactions. ADRs carry prices in US dollars, pay dividends in US dollars, and can be traded like the shares of US-based companies. Each ADR is issued by a US depositary bank and can represent a fraction of a share, a single share, or multiple shares of foreign stock.

[25]There are different types of ADR programs that a foreign company could choose, such as unsponsored share, Level I, Level II, Level III, 144-A and Regulation S. Unsponsored shares are ADRs that trade on the over-the-counter (OTC) market. These shares have no regulatory reporting requirements and are issued in accordance with market demand. Level 1 depositary receipts are the lowest sponsored shares that can be issued. Level I shares can only be traded on the OTC market and the company has minimal reporting requirements with SEC. Level II allows the firms' shares can be listed on a U.S. stock exchange, NYSE, AMEX or NASDAQ. Foreign company that issue a Level 2 program must meet full SEC disclosure requirements and meet the listing requirements of the US stock exchange on which they are listed. In addition, the company is required to file a Form 20-F annually and follow GAAP standards. A Level 3 depositary receipt program is the highest level a foreign company can have. Setting up a Level 3 program means that the foreign company is not only taking some of its shares from its home market and depositing them to be traded in the U.S. but also issuing shares to raise capital. Foreign companies with Level 3 programs will often issue materials that are more informative and are more accommodating to their U.S. shareholders because they rely on them for capital. Rule 144-A and Regulation S are the two restricted programs that foreign companies limit their stock to be traded by only certain individuals. ADR programs operating under one of these 2 rules make up approximately 30% of all issued ADRs.

An owner of an ADR has the right to obtain the foreign stock it represents, but US investors usually find it more convenient simply to own the ADR. The price of an ADR is often close to the price of the foreign stock in its home market, adjusted for the ratio of ADRs to foreign company shares. Depositary banks have numerous responsibilities to an ADR holder and to the non-US company the ADR represents. The first ADR was introduced by JPMorgan in 1927, for the British retailer Selfridges & Co. The largest depositary bank is the Bank of New York. Individual shares of a foreign corporation represented by an ADR are called American Depositary Shares (ADS).

ETFs emerge in the late 1990's while the history of ADRs and CEFs are longer than that of ETFs. ETFs are desirable investment vehicles for both institutional and private investors. ETFs are more accessible and convenient trading vehicles for smaller orders or orders motivated by liquidity needs. The presence of liquidity traders may attract informed traders to take advantage of potential profit opportunities in the ETF market. CEF is more likely to be dominated by behaviour bias individual investors while ADR is more likely to be dominated by institutional traders. Three securities from the same country listed in US should be correlated but different in trading. It is quite interesting to investigate the behaviour of the three securities and will provide a good guide for US investors who want to invest in foreign markets.

3.2.2 Sample Construction

The primary dataset I use to study the trading of the triplets, ADR, ETF, and CEF is obtained by a special construction. First, I obtain the details of all the ADRs, CEFs and ETFs of foreign equities from the website of NYSE, AMEX and NASDAQ and Center for Research in Security Prices (CRSP) dataset. I choose the countries or regions with at least two types of securities listed in US. There are 29 countries and four regions included in the dataset. For ADR, I exclude those ADRs that belong to unsponsored share, Level I, 144-A and Regulation S because they are not allowed to be traded in a stock exchange or in public. For each country, I choose the ADR with the most heavily traded and highest turnover as the leading ADR of that country. For ETF and CEF, I also use the same standard to choose the one with the highest volume and turnover. So I pair up the securities together and choose the longest overlapping period for the securies for each country. The sample period is from March 18th, 1996 to Jan. 5th, 2007 for most of the countries and regions except some cases. The sample period for each country is summarized in Table 3.1.

Second, I obtain the tick-by-tick trading and bid-ask dataset for the three securities of each country from the Trades and Quotes (TAQ) database. The quote data are from the NBBO (National Best Bids and Offers) quote database. To construct the sample of intra-day trading, I divide each trading day into 78 five-minute intervals from 9:30 a.m. to 16:00 p.m.. I exclude overnight intervals from my analysis. Table 3.2 summarize the statistics on the trading activities by type of securities and country. It lists the numbers of the trades, mean price, spread $((bid-ask)/((bid+ask)/2))$, depth $((bidsiz+asksiz)/2)$, volatility, return, volume, trading value, fraction of trading volume and fraction of trading value among the triplets of the Leading ADR, ETF, and CEF for each country and region. The average (median) numbers of trades in the sample are 3,010,542 for leading ADR, 302,728 for ETF, and 190,040 for CEF. The mean (median) market value of all investor holdings in US is \$32,128 (\$25,143) for leading ADRs, \$31,707 (\$31,854) for ETFs, and \$13,223 (\$11,541) for CEFs. Bailey, Kumar, and Ng

(2007) show that the mean (median) market value of individual investor holdings is \$16,383 (\$5,707) for international open end mutual funds, \$10,877 (\$4,849) for ADRs and other foreign-incorporated stocks, and \$11,771 (\$5,540) for closed end country funds from a database of individual investors with accounts at a major U.S. discount broker from January 1991 to November 1996. It indirectly verifies that CEF is more likely to be dominated by individual investors while ADR is more likely to be dominated by institutional traders if I assume that all investors in US mainly compose of institutional investors and individual investors. I define the fraction of trading volume as the trading volume of one security divided by the total trading volume of the three securities. The fraction of trading value is defined as the trading value of one security divided by the total trading value of the three securities. The average fraction of trading volume over all the countries and regions in the datasets is 83.07% for the leading ADR, 29.70% for the ETF, and 8.51% for the CEF. The average trading value is 75.79% for the leading ADR, 25.82% for the ETF, and 19.29% for the CEF. The fraction of trading volume (value) in the emerging Asia countries is on average 54.52% (41.14%) for ETF. It is higher than leading ADR and CEF. The trading on the leading ADR is on average heavier than on the ETF and CEF. Since I am interested in the intraday trading and behavious of the three securities, I use the midquote return and focus more on shorter horizon dynamics. The average return of the leading ADR is higher than that of the ETF but there are 14 out of 20 countries that have higher returns on ETF than the leading ADR. There are 14 out of 20 countries that have higher returns on ETF than CEF. There are 12 out of 23 countries that have higher returns on ADR than CEF. On average, the performance of ETF is better than ADR and CEF. It will be quite interesting to look at the correlations of the leading

ADR, ETF, and CEF.

I conduct my analysis on two types of trades. First, I use all trades, regardless of who initiates the trade. Since I am concerned about the impact of trades by the US-based investors on returns and prices, I would like to identify those trades that are most likely to affect prices. Thus, I just consider the price-setting trades that have been used recently in the literature. It is better to obtain a dataset that have the exact classification about buys and sells according the investor information (Choe, Kho, and Stulze (1999) and Kaniel, Saar, and Titman (2006)). Yet due to the limit access of the dataset, I use the algorithm developed by Lee and Ready (1991) to define the trade directions as a buy or a sell. This algorithm compares transaction prices to the mid-quote five seconds before the transaction took place[26]. The trade data are matched with the previous NBBO quote data and all the variables are analyzed in the 5-minute time interval. Orders are timestamped to indicate the time of arrival at the exchange while trades indicate the time the order was executed. Then I get the the matched buy and sell orders, the size and price of the trade, and other information. Table 2.3 summarize the statistics on trading activity by trade type and Country. It lists mean price, spread, depth, volume, trading value, volatility, and return of a buyer-initiated trade and a seller-initiated trade among the Leading ADR, ETF, and CEF for each country and region. The average trade value of ADR (ETF, CEF) is $17,056.611 ($16,519.517, $6,291.625) for buys and $13,891.317 ($14,881.649, $6,364.273) for sells. Kaniel, Saar, and Titman (2006) report the average (median) trade size for an individual in their sample is $15,822 ($13,243). And Barber and Odean (2000) report an average trade size of $13,707 for sells and $11,205 for buys (but much smaller medians,

[26]Ellis, Michaely and O'hara (2000) evaluate how well the Lee and Ready algorithm performs and find that it is 81.05% accurate.

$5,738 and $4,988, respectively). In Barber and Odean (2005), the average trade size in the sample of individuals who use a full-service broker between 1997 and 1999 is $15,209 for buys and $21,169 for sells. The sample I construct is consistent with their report. But my sample contains ADR, ETF, and CEF from the 29 countries and 4 regions and their sample mostly covers common domestic stocks. On average, the average returns is negative for buys and positive for sells. That is the sellers do better than buyers in the three securities, ADR, ETF, and CEF.

3.3 DO THE LEADING ADR, ETF, AND CEF TRADE DIFFERENTLY?

3.3.1 Do the Leading ADR, ETF, and CEF trade at a disadvantage price over the others?

I want to examine how the type of trade differs among the three securites. I computing relative price ratios following Choe, Kho, and Stulz (2005) and Bailey, Mao and Sirodom (2006). Relative to the average buy (sell) price for a particular stock and time, I determine which type of security typically pays (receives) a relatively low (high) price, implying a well timed and executed trade. Each security typically attracts different types of investors, institution investors and individual investors. ETFs are more accessible and more convenient trading vehicles for smaller orders or orders motivated by liquidity needs. The presence of liquidity traders may attract informed traders to take advantage of potential profit opportunities in the ETF market. The closed end fund is more likely to be dominated by behaviorally biased individual small investors while ADR is more likely to be dominated by institutional traders. If I could determine which type of security trades at a better transaction price, it is possible for me to link trades and relative transaction prices with investors and transaction prices.

Following Choe, Kho, and Stulz (2005) and Bailey, Mao and Sirodom (2006), I compute the volume-weighted average price for each security A_{it} in 5 minute interval and then then compute the volume-weighted average price for the certain type of trade for the same security over the same time interval B_{it}. The volume-weighted average price ratio is defined as B_{it}/A_{it} for the security during the certain time interval. A price ratio greater (less) than one for the purchases (sales) of a particular type of security suggests that this type of security buys (sells) on average at a price above (below) the average price on that day. Holding everything else equal, security X is at disadvantage relative to security Y for purchases (sales) if security X buys (sells) at a higher (lower) price ratio than security Y. Table 4 summarizes the ralative price ratio of the triplets (Leading ADR, ETF and CEF) for certain type of trade. The relative price ratios are multiplied by 100. Two hypothesis tests are investigated in table 3.4. One is whether the relative price ratio of one security is significantly different from 100 and the other is whether the relative price ratios among the three securities are significantly different from the other.

My results are quite different from Choe, Kho, and Stulz (2005) and Bailey, Mao and Sirodom (2006). They are interested in whether different types of investors trade at different transaction prices over all the securities or different trading boards. They have the dataset with the information about the buys and sells. The limitation of my approach is the classification of buys and sells by Lee and Ready (1991) might miss some important trades of the investors. Yet, I still get some interesting results from this approach. If a certain type of investors invests in a certain type of securities, will their performance be different in different countries? Leading ADR, on average, buys at a higher price except Japan, China, Belgium and Brazil and sells at a lower price than ETF except Japan, China, and

Belgium. ETF buys at a lower price than CEF in 9 out of 20 countries. They are China, Italy, Spain, France, Mexico, South Africa, Canada, Europe, and Emerging market. ETF sells at a higher price relative to CEF in China, Italy, France, Mexico, South Africa, Canada, Europe, and Emerging market. Leading ADR buys at a higer price relative to CEF except Japan, China, Philippine, Italy, Russia, Turkey, Chile, Mexico. Leading ADR sells at a lower price relative to CEF except Japan, China, Philippine, and Russia.

First, I find evidence that the investors are at a disadvantage investing in ADR relative to in ETF on average. The average disadvantage of investing in ADR relative to ETF is of the order of 11 basis points for purchases and 12 basis points for sales. This means that on a roundtrip trade the investors in investing in ADR face greater transaction costs of the order of 23 basis points compared with investors in investing in ETF. Second, investors are at a disadvantage investing in ADR relative to in CEF on average. The average disadvantage of investing in ADR relative to CEF is of the order of 10 basis points for purchases and 13 basis points for sales. This means that on a roundtrip trade the investors in investing in ADR face greater transaction costs of the order of 23 basis points compared with investors in investing in CEF. Third, there are no significant evidence to show whether the investors are at a disadvantage investing in ETF relative to in CEF on average. The average disadvantage of investing in CEF relative to ETF is of the order of 1 basis points for purchases but the average disadvantage of investing in ETF relative to CEF is of the order of 1 basis points for sales. I could also infer that institution investors trade at a disvantageous price relative to individual investors on average. Those results might come from the difference of Leading ADR, ETF, and CEF.

3.3.2 Correlation of the trades: Leads and Lags of the Three Securites

In my sample, the paired leading ADR, ETF, and CEF are from the same country and their trading behaviour might be corrlated by intuition. In order to investigate the trading behaviour of the three securities, the natural questions are (1) how trading differs, in real time, among the three related securities? (2) what is the relative relation of returns, quoted spread, volume and volatility among the three securities?

I use the VAR model to estimate the relation of return, quoted spread, volume and volatility among the three types of securites. Vector X_t can be expressed in terms of current and lagged innovations:

$$X_t = A_0 + \sum_{j=1}^{k} A_j X_{t-j} + u_t \tag{3.3.1}$$

Where $X_t = \{V_t^1, V_t^2, V_t^3\}$ represents return, quoted spread, volume and volatility of the leading ADR, ETF, and CEF respectively. Also I use granger-causality test to show whether the return, quoted spread, volume and volatility of one security granger cause those of the other security.

Table 3.5 presents the results of the VAR on the returns of the leading ADR, ETF, and CEF. And $\chi^2(6)$ show the results of the Granger Causality test for the relations of the returns of the leading ADR, ETF, and CEF. It only presents the coefficients of the returns of one security on the lag returns of the other two for last period and the past 6th period. The returns of leading ADR are significantly positively related to the past returns of ETF (except Israel, Canada and emerging market) and CEF. The returns of ETF are significantly positively related to the past returns of leading ADR (except Israel, Canada and emerging market) and CEF (except Canada). The returns of CEF are significantly positively related to the past returns of leading ADR (except China and Israel) and ETF. The granger causality test shows that the past returns of the other two securites granger cause the current returns of one security. On average, the returns of leading ADR are 2.6% related to the past returns of ETF and 2.7% related to the past returns of CEF. The returns of ETF are 0.8% related to the past returns of leading ADR and 1.2% related to the past returns of CEF. The returns of CEF are 0.6% related to the past returns of leading ADR and 1.4% related to the past returns of ETF. The results verify our hypothesis that leading ADR, ETF, and CEF are correlated and we could forecast the future returns of one security by the past returns of the other two. That is, if we observe increasing returns of one security, we could forecast the directions of the other two.

Table 3.6 presents the results of the VAR on the volumes of the leading ADR, ETF, and CEF across the countries. And $\chi^2(6)$ show the results of the Granger Causality test for the relations of the volumes of the leading ADR, ETF, and CEF. It only presents the coefficients of the volumes of one security on the lag returns of the other two for last period and the past 6th period. There are not a clear relation of the current volume and the past volume among the leading ADR, ETF, and CEF across all the countries. The volume of leading ADR is positively related to the past volume of ETF except Singapore, Hongkong, India for the Asian countries, Russia, Chile, and Israel. The volume of leading ADR is negatively related to the past volume of ETF for the European countries. The volume of leading ADR is positively related to the past volume of CEF except Australia, Singapore, Spain, and Canada. The volume of ETF is negatively related to the past volume of leading ADR except Australia, Japan, China, India, Korea, Taiwan, UK, Russia, and Israel. The volume of CEF is positively related to the past volume of leading ADR except Australia, Singapore, Japan, Taiwan, and Canada. The patterns of trading volume among the different countries are diversified.

Table 3.7 presents the results of the VAR on the volatilities of the leading ADR, ETF, and CEF across the countries. And $\chi^2(6)$ show the results of the Granger Causality test for the relations of the volatilities of the leading ADR, ETF, and CEF. On average, the volatilities of one security is positively related to the past volatilities of the other two. There are some exceptions. The volatilities of leading ADR is negatively related to the past volatilities of ETF for South Africa and Canada and vice versa. On average, the volatilities of leading ADR are 2.75% related to the past volatilities of ETF and 3.43% related to the past volatilities of CEF. The volatilities of ETF are 1.56% related to the past volatilities of leading ADR and 1.11% related to the past volatilities of CEF. The volatilities of CEF are 1.25% related to the past volatilities of leading ADR and 1.35% related to the past volatilities of ETF. In short, the risks associated with the trading are approaching the same direction among the three securities leading ADR, ETF, and CEF. Table 8 presents the results of the VAR on the quoted spreads of the leading ADR, ETF, and CEF across the countries. And $\chi^2(6)$show the results of the Granger Causality test for the relations of the quoted spreads of the leading ADR, ETF, and CEF. On average, the spreads of one security is positive related to the past spreads of the other two securities. The spreads of leading ADR is negatively related to the past spreads of ETF for India, Belgium, Spain, Chile, Israel, South Africa, and Latin America. The spreads of ETF is negatively related to the past spreads of leading ADR for Hongkong, India, Spain, and South Africa. The spreads of CEF is negatively related to the past spreads of leading ADR for Germany.

Table 3.5-3.8 present the leads and lags of the relations about the returns, volume, volatilities, and quoted spreads among the three securities, leading ADR, ETF, and CEF. In summary, the trading behaviour of the three securities are highly correlated. The results verify our hypothesis that the three securities leading ADR, ETF, and CEF are correlated and we could forecast the future returns of one security by the past returns of the other two.

3.4 DYNAMIC RELATION BETWEEN ORDER IMBALANCE AND RETURNS AMONG THE THREE SECURITIES

In last section, I get the results that the trading behaviour of the three securities are highly correlated. The main focus of this section is on the concurrent and past order flow-return relation of the three securities. Inferences about this relation are potentially affected by the time-series properties of each variable. In particular, order flow is highly predictable. If net buy-sell imbalances by one security respond systematically to past returns, VAR systems are estimated to get a more complete picture of the dynamics of the effect of returns on net order imbalances.

3.4.1 Regressions of Net Buy-Sell Imbalance and Short-Horizon Returns

In section 3.2, I define the price-setting buys and sells by using the algorithm developed by Lee and Ready (1991). For each 5 minute interval for all the three securities across the countries, I compute price-setting order imbalances by security type by subtracting the "price-setting" sell volume from the price-setting buy volume, and then normalizing by the stock's average 5-minute price-setting volume over the sample period. A "price-setting buy" (sell) trade for one security, for example, is a trade where the buy (sell) order of that security came after the sell-side (buy-side) order that it is matched to, and hence made the trade possible.

VARs have been used by Froot et al. (2001), Karolyi (2002), Dahlquist and

Robertsson (2004) to examine the correlation between inflows and returns. I use the VAR model to estimate the relation of net order imbalances and returns among the three types of securites. Vector Y_t can be expressed in terms of current and lagged innovations:

$$Y_t = A_0 + \sum_{j=1}^{k} A_j Y_{t-j} + u_t \tag{3.4.1}$$

Where $Y_t = \{OIB_t^1, OIB_t^2, OIB_t^3, R_t^1, R_t^2, R_t^3\}$ represents net order imbalances and returns of the leading ADR, ETF, and CEF respectively. The lag length is chosen as $k = 6$ by Akaike and Schwartz-Bayes criteria. Panel A-E of table 3.9 summarize the average coefficients of the VARs across all the countries, the regions of the Asia and Pacific, Europe, Latin America, and Emerging Market when the dependent variables are $OIB_t^1, OIB_t^2, OIB_t^3, R_t^1, R_t^2$,and R_t^3. In Table 3.9, order imbalance (return) is regressed on concurrent and lagged returns (order imbalance) and lagged order imbalance (returns). The first three columns develop the relation between flow and predetermined variables-lagged returns and flow.

First, as shown in Table 3.9, order imbalance is correlated with past order imbalance. Second, order imbalance is strongly dependent on lagged returns. I use order imbalance of ADR as an example. Order imbalance of ADR is 15.33% related on lag order imbalance of ADR, 4.3 basis point on ETF, and 7.3 basis point on CEF. Order imbalance of ADR is 46.16% related on lag returns of ADR, 17.24% on ETF, and 21.76% on CEF. They are both economic and statistically significant. Lagged returns and order imbalances of the three securities explain the variations of the order imbalances. There are some exceptions shown in Panel B-E. The net order imbalances of ADR are negatively related with the past returns of ADR in European and Latin American countries and with the past returns of ETF in Latin American countries.

The column 4-6 of Table 3.9 presents regressions of returns on concurrent and lagged order imbalances. First, returns is correlated with past order imbalance. Second, returns is strongly dependent on lagged returns. I use returns of ADR as an example. Returns of ADR is 33.47% related on lag order imbalance of ADR, 1.08% on ETF, and 1.71% on CEF. Returns of ADR is -18.56% related on lag returns of ADR, 6.0 basis point on ETF, and 3.7 basis point on CEF. They are both economic and statistically significant. Returns of one security are negatively related to Lagged returns of itself and positively related to lag returns of the other two securities.

The association between order flow and returns potentially reflects a causal relation from order flow to returns, but it could also reflect positive feedback trading by investors (returns causing flow), or a joint reaction of both returns and order flow to economic news. The results of VAR model tell us that the trading of the three securities are positively correlated and the buy and sell trades of one security are not only decided by the net order imbalances and past returns of the certain security itself but also the net order imbalances and past returns of the other two securities.

This results makes intraday feedback trading explanations somewhat more plausible. If the increasing returns are observed, the buy trades of one security take place. If the decreasing returns are observed, the sell trades of one security take place. On average, the returns of one security are positively correlated with the past net order imbalances, past returns of the other two securities and negatively correlated with the past returns of the same type of security. The results of these regressions indicate that the trading by the three securities is a powerful predictor of future returns of the three securities themselves.

3.4.2 Trading Strategies and Robustness Check

Most research in the literature are focusing on the relation between the net trading and returns among different type of investors institution, individual, and foreign investors.Those research above have the dataset that could classify the traders as institution, individual and foreign investors for some certain countries. They investigate stock returns around the time of trades initiated by a certain type of investors such as foreign investors. In this paper, I want to investigate the relation between the net trading and returns among the three securities leading ADR, ETF, and CEF across the countries. ETFs are more accessible and more convenient trading vehicles for smaller orders or orders motivated by liquidity needs.

The presence of liquidity traders may attract informed traders to take advantage of potential profit opportunities in the ETF market. The closed end fund is more likely to be dominated by behaviorally biased individual small investors while ADR is more likely to be dominated by institutional traders. In this sense I could infer some interesting results from the relation between the net trading and returns among the different type of securities to the different type of investors.

In the last section, I get the results that the order imbalances and returns are correlated with the past order imbalances and returns. I want to further check the trading behavior among the three securities. I examine the extent to which intense net buying or selling by one security is related to the three securities' past returns and the extent to which such intense net trading by certain type of securities predicts future returns. One methodology I use is to investigate the cumulative returns around the largest and smallest buying and selling activity of the three securities leading ADR, ETF, and CEF.

The results are summarized in table 3.11. For each security, I select the trades with the highest 5% and lowest 5% trading volume. All the trades are time-stamped in 5-minute interval. Then I calculate the average cumulative midquote returns of the three securities before and after the heaviest and lightest trading of one certain type of security. Panel B presents the cumulative midquote returns of leading ADR, ETF, and CEF around the largest and smallest buying activities of one security. I show the average cumulative midquote returns over windows $[-k,-1], 0, [1,k], [-j,0]$, and $[0,j]$, $k = 1, 5, 10, 15, 20$, and $j = 5, 10, 20$. The intense buy trades of one security take place when the returns of that certain type of security are increasing. Associated with the largest buying activity, the returns of the other two securities are also increasing. There exists abnormal returns around the intense buy trades. Panel C presents the cumulative midquote returns of leading ADR, ETF, and CEF around the largest v.s smallest selling activities of one security. The intense sell trades of one security take place when the returns of that certain type of security are decreasing. Associated with the largest selling activity, the returns of the other two securities are also decreasing. There exists abnormal returns around the intense sell trades as well. This results are very important. I find that the buy trades of one security take place after returns increase and sell trades after returns decrease.

Part (d) of Panel B and C in Table 3.11 present the relative difference of returns between the largest and smallest trading among the three securities. I calculate the average cumulative midquote returns over windows $[-k, 0], 0, [0, k]$ and $k = 5, 10, 20$. Panel B part (d) show that the cumulative returns are higher at smallest buying than at largest buying. ETF has always higher returns than ADR and CEF no matter when it is heavily or lightly buying. ADR has a higher return than CEF when heavily buying and a lower return than CEF when lightly buying.

Panel C part (d) show that the cumulative returns are higher at largest selling than at smallest selling. ETF has always lower returns than ADR and CEF no matter when it is heavily or lightly selling. ADR has a lowher return than CEF when heavily selling and a higher return than CEF when lightly selling. The cumulative returns of CEF around the sell trades are higher than that of leading ADR and ETF. I could infer that the individual investors do better than institution investors when selling.

I also investigate the average price around the largest and smallest buying and selling activity of the three securities leading ADR, ETF, and CEF. The results are summarized in table 3.12. Using the same method, I calculate the average prices of the three securities over windows $[-k, -1], 0, [1, k], [-j, 0]$, and $[0, j]$, $k = 1, 5, 10, 15, 20$, and $j = 5, 10, 20$, which presents the average prices just before and after the largest v.s. smallest trades of one security. Panel B show that the intense buy trades of one security take place when price increases. Associated with the largest buying activity, the prices of the other two securities are decreasing on the opposite. There exists abnormal prices around the intense buy trades. Panel C show that the intense sell trades of one security take place when price decreases. Associated with the largest selling activity, the prices of the other two securities are increasing on the opposite. There exists abnormal prices around the intense sell trades as well. In short, investors buy one security when price increases and sell when price decreases. So the trading of leading ADR, ETF, and CEF follows the positive feedback trading.

3.4.3 Impulse Response and Predictibility of Order Imbalance and Returns

In this section, I want to investigate (1) the impulse response between order imbalances and returns; (2) the predictibility of past returns and order imbalances for future returns of three securities.

To understand the dynamic properties of order imbalance and returns, we compute impulse response functions (IRFs) for order imbalance and returns. The IRF traces the impact of a one-time, unit standard deviation, positive shock to one variable on the current and future values of order imbalances and returns of three securities. Since the innovations are correlated (as we shall show), they are orthogonalized. Specifically, the inverse of the Cholesky decomposition factor of the residual covariance matrix is used to orthogonalize the impulses. When computing the IRF, we need to choose a specific ordering of the endogenous variables since different orderings may result in different responses. Our focus is on the dynamic relation between order imbalances and returns. I choose the order imbalances as the first in the ordering then returns last[27]. The following ordering I use to compute the IRFs is $OIBADR$, $OIBETF$, $OIBCEF$, $RETURNADR$, $RETUREETF, RETURECEF$.

The contemporaneous and past correlations of order imbalance and return innovations, reported in Table 3.10, show that order imbalances and returns mostly have positive correlations with contemporaneous order imbalance and returns among three securities. However, order imbalances and returns mostly have negative correlations with past order imbalance and returns. Figure 3.1 illustrate the impulse response of order imbalance and returns to a unit standard deviation shock of or-

[27] I don't know the theoretical guidance regarding the relative ordering of returns and order imbalances and, in any case, it doesn't affect the empirical results.

der imbalance and returns. Monte Carlo two-standard-error bands are provided to gauge the statistical significance of the responses. In particular, lagged returns of ADR have a coefficient of 0.4616, with a t-statistic of 18. Thus, a one-standard deviation shock to returns is associated with an 0.46 of one standard deviation shock to order imbalance of ADR on the following period. Figure 1a-1f show that the future order imbalance and returns go up if they face a positive unit standard deviation shock of order imbalance and returns. It reinforces the positive relation between order imbalance and returns. A positive correlation suggests that net flows anticipate future fund returns.

Since I use the VAR model to estimate the relation of net order imbalances and returns among three types of securites in the last section, I can use the modified model to predict future returns. Vector Y_{t+1}can be expressed in terms of current and lagged innovations:

$$Y_{t+1} = A_0 + \sum_{j=1}^{k} A_j Y_{t-j+1} + u_t \tag{2.4.2}$$

Where $Y_t = \{OIB_t^1, OIB_t^2, OIB_t^3, R_t^1, R_t^2, R_t^3\}, j = 1, 2, \cdots, 6$,represents net order imbalances and returns of the leading ADR, ETF, and CEF respectively. Figure 3.2 show the forcasting results of order imbalances and returns. Figure 3.2a show the future order flow of ADR goes down. Figure 3.2b and 3.2c show the future order flow of ETF and CEF go up. Figure 3.2d-3.2f show the future returns go down first then go up again.

3.5 DISCUSSION ON TRADING BEHAVIOR OF ADR, ETF, AND CEF

3.5.1 Liquidity as a driver of Returns and Order Flow

How can I explain the trading bahavior of ADR, ETF, and CEF? It might be due to the liquidity, information or behaviour reasons. First, I do some test on the relationship between liquidity and trading of the three securities leading ADR, ETF, and CEF. Admati and Pfleiderer (1988) show that informed investors seek to execute their trades at times when the market is liquid and active to minimize market impact and to prevent other market participants inferring their information. I hypothesize that the investors who want to invest in foreign quities seek to execute their trades at times and places when liquidity is relatively higher, that is, the bid-ask spread is lower and depth is higher.

I investigate the average quoted spreads and depths around the largest and smallest buying and selling activity of the three securities leading ADR, ETF, and CEF. For each security, I select the trades with the highest 5% and lowest 5% trading volume. All the trades are time-stamped in 5-minute interval. Quote spread and depth are computed as $((bid-ask)/((bid+ask)/2))$, depth $((bidsiz+asksiz)/2)$ respectively. Then I calculate the average quote spreads and depths of the three securities over windows $[-k,-1], 0, [1,k], [-j,0]$, and $[0,j]$, $k = 1, 5, 10, 15, 20$, and $j = 5, 10, 20$, which presents the average quote spreads just before and after the largest v.s. smallest trades of one security. The results are summarized in the table 3.13 and 3.14. If our hypothesis is correct, we should find that liquidity (proxied with quoted spread and depth) is particularly high just before the heaviest trading events, and liquidity is particularly low just before the lightest trading events. The results from table 3.12, I don't find the strong evidence to support my hypothesis trading in investing in the leading ADR, ETF, and CEF takes place when liquidity is relatively higher. When the trading of the three securities are extremely heavy, the bid-ask spread is larger than the spread when the trading of the three securities is very light. Yet the results of table 3.13 support my hypothesis. When the trading of the three securities are extremely heavy, the depth is larger than the spread when the trading of the three securities is very light. So the evidence provided by table 3.12 and 3.13 are not enough or persuasive to explain the trading behaviour of the leading ADR, ETF, and CEF.

3.5.2 Positive Feedback Trading and Information

Information Returns and order flow could move together in response to new information that is relevant for valuation. Brennan and Cao (1996) show mutual fund investors are relatively uninformed about the distribution of returns on the risky asset. Thus, after news is released, mutual fund investors are net buyers (sellers) in response to public release of good (bad) news. Although the model does not explicitly predict that flow will lag returns, Brennan (1998) argues that a lag of one or several days is consistent with information driving returns and flow, if some investors do not stay attuned to the latest news.

There are related literature on trading across markets and information. Eun and Shim (1989) study daily data from a number of exchanges around the world and find that shocks to U.S. equity markets are transmitted to other equity markets, but not vice versa. Hamao, Masulis, and Ng (1990) use open-to-close and close-to-close data and find that both volatility and return innovation spill across markets. These lagged effects appear to be largely due to the informational efficiency of the U.S. market at incorporating information about shocks common to several markets. Craig, Dravid, and Richardson (1995) find that Japanese Nikkei index futures traded on the CME in the U.S. provide complete information about contemporaneous overnight Japanese index returns. Karolyi and Stulz (1996) use Japanese ADRs to explore whether the magnitude of the co-movement of Japanese stocks with the U.S. market can be explained via rnacroeconornic factors. They find that the contemporaneous movement between U.S. stocks and Japanese stocks is strong, but not driven by macroeconomic information. In summary, empirical work on international return behavior suggests that foreign stocks respond contemporaneously or with a lag to common news that they share.

The explanation in the last section can not best explain the trading behaviour of the investors investing in the three securities. Then I want to examine how the trading of the three securities are related to market information and whether the profitability and contribution to price discovery of the trading are consistent with informed trading. The three securities leading ADR, ETF, and CEF are selected from the same country and they may belong to the same information set. My hypothesis is the trading behaviour of the three securities might come from the correlated information set. Griffin, Harris, and Topaloglu (2003) and Bailey, Mao and Sirodom (2006) use the regression of the net order imbalances on lag net order imbalances and lag returns to explore the relation between the trading and infomation. I have already summarized the VAR model of net order imbalances and returns in table 3.9.

The slope coefficients on lagged net order imbalances indicate whether the current net order imbalance is correlated with the previous net order imbalances. The slope coefficients on lagged returns reveal momentum or contrarian trading strategies. The results of VAR model tell us that the trading of the three securities are correlated and the buy and sell trades of one security are not only decided by the net order imbalances and past returns of the certain security itself but also the net order imbalances and past returns of the other two securities. The inclusion of lagged net order imbalances and lagged returns of the three securities allows us to see the trading activity on one security is related to investing on the other two securities, implying that traders use the correlated shared information set of the three securities.

Positive Feedback Trading Most research in the literature are focusing on the relation between the net trading and returns among different type of investors institution, individual, and foreign investors. Dornbusch and Park (1995) contend that the trades of foreign investors are affected by past returns, so that they buy when prices have increased and sell when they have fallen. Such a practice is called positive feedback trading, Bohn and Tesar (1996) and Clark and Berko (1996), show a positive contemporaneous relation between equity flows and stock returns using monthly data. Choe, Kho, and Stulz (1999) find strong evidence of positive feedback trading and herding by foreign investors before the period of Korea's economic crisis. Froot, O'Connell, and Scasholcs (1998) investigate the relation between equity flows and stock index returns with trades of 44 countries using State Street Bank& Trust database, and find strong evidence that flows into a market are positively correlated with lagged returns in that market. They suggest that this positive feedback trading may be evidence that some foreign investors use returns to extract information about future returns. Richards (2005) show positive feedback trading with respect to global, as well as domestic, equity returns using the dataset that contain the aggregate daily trading of all foreign investors in six Asian emerging equity markets.

DeLong, Shleifer, Summers, and Waldmann (1990) show that passive traders and rational speculators trade on firm fundamentals and/or superior information, while positive-feedback traders simply buy when prices rise and sell when prices fall. They provide examples that positive feedback trading can make sense for mutual fund investors. If some stocks react slowly to economic news, then a fund's portfolio return during the day will be positively autocorrelated. Hong and Stein (1999) show that momentum traders can make profit by implementing simple strategies such as trendchasing.

The results in section 3.4 show that investors buy one security when price increases and sell when price decreases. So the trading of leading ADR, ETF, and CEF follows the positive feedback trading. This indicates that investors tend to be momentum traders, and they use returns information from the trading of the three securities to guide the direction of their trading. If the increasing returns are observed, the buy trades of one security take place. If the decreasing returns are observed, the sell trades of one security take place. Positive feedback trading could be a good explanation for the trading behaviour of the investors investing in the three securities.

3.5.3 Trading Bahaviour and Market Efficiency

In the last section, I get the conclusion that the trading bahaviour could be explained by positive-feedback trading and momentum traders. A deeper question is whether this effect improves or hampers the market efficiency. This section investigates this question. Theoretically it is not clear whether or not positive-feedback trading improves the market efficiency. On one hand, positive-feedback trading could improve market efficiency if it speeds up the correction of stock mispricing. Specifically, if market underreact to positive (negative) news and thus underprice (overprice) the past winners (losers), then positive-feedback trading can speed up the price adjustment process by pushing the winners (losers) further to the "correct" level. On the other hand, positive-feedback trading could deteriorate market efficiency by driving stock prices further away from their fundamentals if such trading is unrelated to information on firm fundamentals or is induced by overreaction. This section is an attempt to disentangle the above two possibilities.

De Long, Shleifer, Summers and Waldmann (1990a) show one might conjecture that increased individual trading can make stocks more volatile or riskier. That is the higher returns following an increase in net order imbalances may simply be compensation for the increased risk. Lakonishok, Shleifer, and Vishny (1992) claim that positive-feedback trading and herding have potential to destabilize stock prices; however, they find little supporting evidence in their pension fund sample. Wermers (1999) finds that mutual fund herding stabilizes stock price by speeding up the price adjustment process. I investigate the average return volatilities around the largest and smallest buying and selling activity of the three securities leading ADR, ETF, and CEF. For each security, I select the trades with the highest 5% and lowest 5% trading volume. All the trades are time-stamped in 5-minute interval. Return volatility is computed as absolute value of the midquote return. Then I calculate the average return volatilities of the three securities over windows $[-k,-1], 0, [1,k], [-j,0]$, and $[0,j]$, $k = 1,5,10,15,20$, and $j = 5,10,20$, which presents the average return volatilities just before and after the largest v.s. smallest trades of one security. The results are summarized in the table 3.15. The results from table 3.15 show a pattern that volatility increases prior to intense trading and subsequently decreases. However, the magnitude of the volatility shown in table 3.15 is quite small (about 10% of the average standard deviation), and volatility goes down back to the normal level afterwards. Therefore, it seems that the increase in volatility I observe is too small to explain the trading and returns

I observe. The dataset I use is at a tick-by-tick high frequency and the increase in volatility might be temporary at this frequency. So the evidence of empirical results could not reject the hypothesis that positive-feedback trading improves market efficiency.

3.6 CONCLUSION

This paper examines the trading behaviours among the related foreign securities ADR, ETF, and CEF. A summary of the major findings in this paper is as follows. First, I find that ADR trades at a relative disadvantage transaction price in comparison to ETF and CEF on average.

Second, I use the VAR model to estimate the relation of return, volume, liquidity and volatility among the three types of securites. On average, the returns, volatilities and liquidities of one security are positively related to the past returns, volatilities and liquidities of the other two. The results verify our hypothesis that the trading behaviours of leading ADR, ETF, and CEF are correlated.

Third, I examine the short-horizon dynamic relation between the order imbalance and both past and subsequent returns by type of securities using high-frequency intraday data. I find that the investors buy when returns and prices increase and sell when returns and prices decrease. The trading of leading ADR, ETF, and CEF follows the positive feedback trading. The results show that the trading of the three securities are positively correlated and the buy and sell trades of one security are not only decided by past order imbalances and returns of the certain security itself but also by past order imbalances and returns of the other two securities. Furthermore, the past order imbalances and returns of the three securities can do a good job in predicting future returns of leading ADR, ETF, and CEF.

Fourth, I explain the trading bahaviour of leading ADR, ETF, and CEF. I examine the average quoted spreads, depths and volatilities around the largest and smallest buying and selling activity of the three securities leading ADR, ETF, and CEF. There is not persuasive evidence on the liquidity reasons and the compensation for the increased risk to explain the trading behaviour of three securities. Positive feedback trading bahavior indicates that investors tend to be momentum traders, and they use the correlated shared information set from the trading of the three securities to guide the direction of their trading.

APPENDIX

Table 3.1 The Sample Period for the Selected Leading ADR, ETF, and CEF

This table summarizes the Ticker of the selected Leading ADR, ETF, and CEF for each country. I obtain the details of the ADRs, CEFs and ETFs from the website of NYSE, AMEX and NASDAQ and CRSP dataset. I choose the countries or regions with at least two types of securities listed in US. There are 29 countries and four regions included in the dataset. For each country, I choose the three securities with the most heavily traded and highest turnover for that country. Since the three securities were listed in US at the different time, I choose the longest overlapping period of the three securities for every country as the sample period of the dataset. It is shown in the starting date and ending date.

Country	Leading ADR	ETF	CEF	Starting Date	Ending Date
Australia	BHP	EWA	IAF	3/18/1996	1/5/2007
Singapore	CHRT	EWS	SGF	11/1/1999	1/5/2007
Japan	SNE	EWJ	JEQ	3/18/1996	1/5/2007
China	PTR	FXI	CHN	10/8/2004	1/5/2007
HongKong	ATS	EWH		12/17/1996	1/5/2007
India	INFY		IFN	3/11/1999	1/5/2007
Korea	KTC	EWY	KF	5/12/2000	1/5/2007
Malaysia		EWM	MF	3/18/1996	1/5/2007
Taiwan	TSM	EWT	TWN	6/23/2000	1/5/2007
Indonesia	TLK		IF	11/16/1995	1/5/2007
Philippine	PHI		FPF	10/19/1994	6/18/2003
Germany	DT	EWG	GF	11/18/1996	1/5/2007
Belgium	DEG	EWK		4/26/2001	1/5/2007
Italy	E	EWI	ITA	3/18/1996	2/13/2003
Netherlands	PHG	EWN		3/18/1996	1/5/2007
Sweden	ERIC	EWD		3/18/1996	1/5/2007
Ireland	ELN		IRL	1/4/1993	1/5/2007
Spain	TEF	EWP	SNF	3/18/1996	1/5/2007
Switzerland	NVS	EWL	SWZ	5/11/2000	1/5/2007
France	ALU	EWQ	FRF	3/18/1996	6/18/2004
UK	VOD	EWU		3/18/1996	1/5/2007
Russia	VIP		TRF	11/15/1996	1/5/2007
Turkey	TKC		TKF	7/11/2000	1/5/2007
Chile	ENI		CH	1/4/1993	1/5/2007
Brazil	PBR	EWZ	BZF	8/10/2000	6/2/2006
Mexico	TMX	EWW	MXF	3/18/1996	1/5/2007
ISRAEL	TEVA		ISL	1/4/1993	1/5/2007
South Africa	AU	EZA	ASA	8/5/1998	1/5/2007
Canada	ABX	EWC	CEF	3/18/1996	1/5/2007
Asia		EPP	APF	10/26/2001	1/5/2007
Europe		IEV	CEE	7/28/2000	1/5/2007
Latin America		ILF	LDF	10/26/2001	1/5/2007
EM		EEM	TEI	4/11/2003	1/5/2007

Table 3.2 Summary Statistics on Trading Activity by Security Type and Origin of Country

Table 2 lists the numbers of the trades, mean price, spread ((bid-ask)/((bid+ask)/2)), depth ((bidsize+asksize)/2), volatility, return, volume, trading value, fraction of trading volume and fraction of trading value among the triplets of the Leading ADR, ETF, and CEF for each country and region, in Panel A, B, and C respectively. I obtain the tick-by-tick trading and bid-ask dataset for the three securities of each country from the Trades and Quotes (TAQ) database. The quote data are from the NBBO (National Best Bids and Offers) quote database. I divide each trading day into 78 five-minute intervals from 9:30 a.m. to 16:00 p.m. I exclude overnight intervals from my analysis.

Panel A. Leading ADR

Country	#Trades	Mean Price	Mean spread	Mean Depth	Mean Volatility (10^{-4})	Mean Return (10^{-4})	Mean Volume	Mean Trading Value	Fraction of Trading Volume(%)	Fraction of Trading Value(%)
Australia	2127776	34.882	0.100	18.395	1.367	-0.0038	598.170	19645.450	92.844	69.121
Singapore	917764	21.994	0.1061	8.1974	9.330	-0.0225	730.940	19689.730	86.950	68.809
Japan	19487936	54.315	0.2468	11.4660	3.022	0.0102	637.610	34379.320	68.895	40.148
China	852099	93.305	0.2526	5.2962	2.003	0.0026	314.709	28178.670	66.363	66.733
HongKong	75305	4.621	0.2005	26.2212	62.190	-0.5646	1576.7300	8633.070	5.163	16.581
India	750675	72.523	0.2162	3.2743	5.050	0.0011	239.539	17289.370	88.790	69.170
Korea	934483	21.673	0.2064	24.4254	3.655	-0.0035	1219.350	26665.630	43.369	55.298
Malaysia										
Taiwan	4595104	10.617	0.072	140.231	3.588	0.0009	2148.210	23086.500	80.016	78.029
Indonesia	46305	20.234	0.3510	44.7850	11.629	0.0278	1310.600	17054.090	96.301	93.453
Philippine	22679	24.208	0.3214	26.4760	12.455	0.1448	2265.000	62369.560	83.291	74.995
Germany	1328952	20.771	0.1273	48.6435	5.758	-0.0015	1512.880	35142.600	78.064	68.017
Belgium	84333	56.104	0.3828	5.6135	10.215	0.0954	369.330	19510.070	83.421	73.146
Italy	149850	64.057	0.3549	10.3397	11.082	0.0771	943.670	56180.250	94.392	80.470
Netherlands	44423	37.325	0.1912	20.2450	4.890	0.0022	1061.620	43512.260	98.716	96.949
Sweden	11873790	23.784	0.0452	90.2706	7.997	0.0007	1371.660	22981.320	99.360	96.290
Ireland	6759351	18.215	0.1174	35.5389	6.981	-0.0019	1388.280	24180.780	99.203	97.015
Spain	97196	51.582	0.3202	16.0620	5.204	0.0241	1076.600	61914.390	92.218	85.338
Switzerland	1611990	48.651	0.2015	16.6570	2.077	0.0057	734.540	34281.050	97.696	88.841
France	1188823	26.163	0.219	45.672	10.338	-0.0028	2088.950	54819.640	97.312	91.247
UK	3564548	33.444	0.145	43.307	3.896	0.0007	1815.480	61587.070	97.653	92.851
Russia	1536272	52.226	0.289	7.090	4.887	0.0000	553.940	24963.640	88.651	77.278
Turkey	432133	15.258	0.234	26.679	7.023	0.0090	948.800	12461.190	79.624	67.955
Chile	429233	12.297	0.180	26.512	9.008	-0.0022	1644.610	25324.220	64.750	60.814
Brazil	1936913	54.713	0.246	11.322	2.831	0.0048	931.950	37629.050	82.803	77.830
Mexico	2862338	36.191	0.161	38.532	3.570	-0.0014	1672.240	69554.850	78.450	72.843
ISRAEL	13028675	40.558	0.054	9.100	2.303	0.0005	405.070	16963.190	99.843	96.667
South Africa	1899946	41.925	0.177	6.965	2.747	-0.0018	468.040	19151.000	87.704	81.113
Canada	5656297	24.481	0.086	33.224	3.610	0.00004	1019.100	22435.310	94.117	85.015
Mean	**3010542**	**36.290**	**0.200**	**28.591**	**7.811**	**-0.007**	**1108.844**	**32127.974**	**83.070**	**75.786**

Table 3.2 (Continued)

Panel B. ETF

Country	#Trades	Mean Price	Mean spread	Mean Depth	Mean Volatility (10^{-4}))	Mean Return (10^{-4})	Mean Volume	Mean Trading Value	Fraction of Trading Volume(%)	Fraction of Trading Value(%)
Australia	248018	19.377	0.155	38.364	1.279	-0.0455	875.630	16094.170	5.982	14.704
Singapore	305436	8.845	0.0937	55.4477	9.051	0.0147	1386.540	11608.040	11.637	20.222
Japan	118455	11.399	0.0173	721.0010	0.540	0.0000	604.240	7150.640	0.285	5.957
China	470376	80.364	0.1615	13.8654	2.295	0.0270	471.826	36192.150	31.553	23.541
HongKong	502062	12.731	0.1271	51.7624	9.032	0.0603	1655.0500	20265.420	94.837	83.419
India										
Korea	529203	41.445	0.1844	22.2676	4.635	0.0196	908.880	34624.910	46.965	27.985
Malaysia	311333	7.265	0.093	82.696	13.154	-0.0168	1987.590	13715.160	80.814	57.295
Taiwan	881999	12.751	0.0646	75.5220	3.417	0.0037	1454.980	18065.740	18.446	13.503
Indonesia										
Philippine										
Germany	307419	21.149	0.1497	49.7754	7.453	0.0142	1164.200	23413.940	18.386	18.505
Belgium	47346	19.861	0.2503	40.9101	14.128	-0.4183	1131.060	21154.210	16.579	26.854
Italy	15092	21.587	0.3782	68.6187	38.429	-2.3767	2146.040	44613.970	3.204	8.635
Netherlands	86586	21.706	0.2690	50.6527	19.341	0.1749	1130.240	24186.890	1.284	3.051
Sweden	74368	24.455	0.2779	46.8127	16.133	-0.0557	909.290	20734.760	0.640	3.710
Ireland										
Spain	68976	40.066	0.2886	48.7252	13.498	0.2916	878.220	31853.500	6.198	6.656
Switzerland	60438	19.236	0.3575	60.6947	16.156	0.1279	978.820	18326.940	1.448	5.911
France	22433	20.675	0.504	56.963	34.666	0.4172	2093.540	43057.280	1.451	3.967
UK	152877	18.744	0.260	59.791	13.223	0.0620	2107.980	36347.470	2.347	7.149
Russia										
Turkey										
Chile										
Brazil	573440	33.385	0.163	53.817	5.310	-0.0098	1665.990	46537.710	14.959	15.246
Mexico	620768	38.902	0.168	20.278	4.860	0.0290	1058.730	35230.390	18.288	16.456
ISRAEL										
South Africa	77400	98.303	0.543	7.440	7.585	0.1628	476.580	45198.680	7.730	9.186
Canada	290746	21.747	0.122	82.449	6.599	0.0442	1249.830	23063.830	4.298	6.175
Asia	152779	97.109	0.359	14.494	5.009	0.1540	560.750	51697.630	92.733	49.314
Europe	147750	77.398	0.331	46.642	9.448	0.0712	875.340	63322.170	66.002	43.071
Latin America	258933	128.178	0.448	8.488	4.682	0.0657	349.140	43300.890	97.214	88.925
EM	2202285	102.707	0.126	14.172	1.175	0.0005	738.540	75011.730	99.271	85.951
Mean	**302728**	**36.204**	**0.248**	**64.464**	**11.844**	**-0.070**	**1212.937**	**31706.501**	**29.702**	**25.815**

Table 3.2 (Continued)

Panel C. Closed-end Fund (CEF)

Country	#Trades	Mean Price	Mean spread	Mean Depth	Mean Volatility (10^{-4})	Mean Return (10^{-4})	Mean Volume	Mean Trading Value	Fraction of Trading Volume(%)	Fraction of Trading Value(%)
Australia	95446	9.722	0.468	23.135	0.550	-0.1523	1006.490	8883.390	1.173	16.175
Singapore	35122	9.341	0.4421	12.1009	27.377	0.1722	883.890	7492.320	1.413	10.969
Japan	1829632	7.748	0.4214	21.8610	28.688	-0.0831	1078.280	8241.940	30.821	53.896
China	84091	29.695	0.3731	5.4387	10.274	0.0151	435.915	12826.920	2.084	9.726
HongKong										
India	660237	38.148	0.4015	8.6084	6.634	0.0320	566.752	17647.770	11.210	30.830
Korea	192079	23.503	0.3035	11.8691	8.583	-0.0271	966.180	18080.120	9.667	16.717
Malaysia	68075	7.888	0.316	22.192	37.516	-0.0656	1055.100	8174.250	19.186	42.705
Taiwan	70017	13.395	0.5100	12.2710	13.563	0.1272	1046.390	13269.800	1.538	8.468
Indonesia	66725	7.527	0.2382	16.1658	45.782	0.0377	942.470	6674.770	3.699	6.547
Philippine	53857	11.062	0.2441	29.9430	37.479	-0.5781	1184.600	11746.800	16.709	25.005
Germany	114544	10.958	0.2926	33.8237	20.998	-0.0930	1290.120	14182.780	3.550	13.479
Belgium										
Italy	20046	12.195	0.3592	34.6330	33.001	-0.7133	1687.740	20934.990	2.404	10.895
Netherlands										
Sweden										
Ireland	60905	16.242	0.4009	13.6160	30.065	0.2321	674.040	9754.600	0.797	2.985
Spain	58375	12.105	0.4102	20.3860	32.786	-0.4425	883.830	11211.050	1.585	8.006
Switzerland	50050	13.733	0.3833	10.5800	15.687	-0.4017	854.400	11335.670	0.856	5.248
France	35229	11.225	0.387	46.741	29.145	-0.4539	1702.080	19116.350	1.237	4.787
UK										
Russia	233903	43.913	0.559	5.132	19.742	0.0896	485.060	17590.430	11.349	22.722
Turkey	103202	16.350	0.462	7.632	19.454	0.0311	648.060	9286.320	20.376	32.045
Chile	122753	23.410	0.407	15.061	22.813	-0.1038	908.960	17875.830	35.250	39.186
Brazil	80204	35.717	0.528	8.382	12.648	0.2512	735.700	24050.630	2.238	6.924
Mexico	239365	17.997	0.283	47.306	16.778	-0.0167	1291.400	21897.340	3.262	10.701
ISRAEL	57878	14.319	0.421	11.055	29.530	0.1091	796.720	11057.460	0.157	3.333
South Africa	237563	47.008	0.330	4.461	6.275	0.0226	347.390	15948.550	11.345	17.152
Canada	343198	6.794	0.147	31.101	12.778	-0.0586	1296.160	8205.150	1.585	8.810
Asia	90866	12.795	0.621	11.095	15.480	0.2042	844.550	9989.920	7.267	50.686
Europe	146375	40.244	0.442	6.237	11.004	0.1299	434.250	15837.710	33.998	56.929
Latin America	44121	21.557	0.327	6.194	15.065	-0.7353	576.260	10970.590	2.786	11.075
EM	127275	13.046	0.356	10.114	10.640	-0.2610	613.040	7963.860	0.729	14.049
Mean	**190040**	**18.844**	**0.387**	**17.398**	**20.369**	**-0.098**	**901.280**	**13223.118**	**8.510**	**19.287**

Table 3.3 Summary Statistics on Trading Activity by Security Type and Country

Table 3 lists mean price, spread ((bid-ask)/((bid+ask)/2)), depth ((bidsize+asksize)/2), volume, trading value, volatility, and return of a buyer-initiated trade and a seller-initiated trade among the Leading ADR, ETF, and CEF for each country and region, in Panel A, B, and C respectively. I use the algorithm developed by Lee and Ready (1991) to define the trade directions as a buy or a sell. This algorithm compares transaction prices to the mid-quote five seconds before the transaction took place. The trade data are matched with the previous NBBO quote data and all the variables are analyzed in the 5-minute time interval.

Panel A. Leading ADR

	Buy Trade							Sell Trade						
Country	Mean Price	Mean spread	Mean Depth	Mean Volume	Mean Trading Value	Mean Volatility (10^{-4})	Mean Return (10^{-2})	Mean Price	Mean spread	Mean Depth	Mean Volume	Mean Trading Value	Mean Volatility (10E-4)	Mean Return (10^{-2})
Australia	18.296	0.0547	10.6694	359.400	11331.490	0.699	-0.0135	14.550	0.0487	7.2008	257.898	8207.940	0.668	0.0136
Singapore	10.750	0.0474	3.9463	365.774	9734.810	4.578	-0.0355	10.919	0.0574	4.0500	351.400	9660.760	4.752	0.0362
Japan	28.549	0.0996	6.4250	334.049	18161.820	1.452	-0.0220	24.065	0.1430	4.7080	287.178	15319.930	1.570	0.0224
China	43.638	0.0798	2.9395	250.982	19030.860	1.000	-0.0142	35.429	0.0804	2.3020	214.262	16626.230	1.003	0.0142
HongKong	2.187	0.0890	11.9416	690.496	3662.070	29.911	-0.1726	2.116	0.0986	13.3068	813.629	4432.790	32.279	0.1662
India	20.422	0.2159	1.6335	292.143	9283.970	2.5172	-0.0061	17.327	0.1818	1.5821	261.794	8108.940	2.5332	0.0062
Korea	11.544	0.0983	13.2830	673.719	14790.950	1.855	-0.0241	9.474	0.1026	10.4462	512.620	11110.040	1.800	0.0242
Malaysia														
Taiwan	5.397	0.0338	73.4082	1100.980	11954.010	1.802	-0.0221	4.414	0.0335	57.6951	878.004	9430.640	1.786	0.0223
Indonesia	10.012	0.0863	24.1892	607.364	8068.090	5.541	-0.0505	9.597	0.2535	18.0153	598.873	7792.780	6.088	0.0517
Philippine	11.700	0.1578	12.9022	1154.020	31985.590	6.316	-0.0599	9.822	0.1304	11.5967	913.029	23820.820	6.139	0.0561
Germany	10.375	0.0595	24.0471	817.856	19290.040	2.811	-0.0213	9.472	0.0618	22.3989	631.625	14255.280	2.947	0.0214
Belgium	22.336	0.1583	2.2956	156.528	7967.870	4.235	-0.0463	33.634	0.2237	3.3007	211.206	11456.570	5.981	0.0475
Italy	35.082	0.2057	5.3035	498.363	29828.940	5.708	-0.0227	27.949	0.1427	4.6547	407.117	24288.340	5.375	0.0227
Netherlands	18.817	0.0918	10.5289	537.922	21936.530	2.398	-0.0238	16.561	0.0908	8.6779	475.306	19041.670	2.492	0.0238
Sweden	11.827	0.0223	45.9775	675.840	11291.170	4.022	-0.0017	10.994	0.0212	42.9417	664.722	10996.670	3.975	0.0017
Ireland	9.293	0.0573	17.6967	694.029	12593.580	3.408	-0.0239	7.665	0.0532	15.0237	607.891	10087.630	3.574	0.0242
Spain	26.487	0.1526	8.2613	591.046	34370.170	2.532	-0.0229	23.772	0.1614	7.2720	451.231	25273.650	2.672	0.0234
Switzerland	27.096	0.0973	9.5601	412.407	19293.700	1.055	-0.0156	20.167	0.1000	6.5466	304.365	14152.4300	1.0214	0.0158
France	13.257	0.113	23.478	1147.790	30486.990	5.197	-0.0429	11.825	0.097	20.421	867.236	22292.270	5.141	0.0426
UK	16.162	0.068	20.020	909.840	31597.610	1.919	-0.0156	15.096	0.069	19.490	808.631	26321.980	1.977	0.0155
Russia	28.200	0.152	3.812	296.676	13519.680	2.457	-0.0257	23.246	0.133	3.126	243.940	10969.560	2.429	0.0256
Turkey	8.587	0.121	14.166	505.947	6796.690	3.505	-0.0688	6.339	0.110	11.446	416.016	5341.070	3.518	0.0684
Chile	6.450	0.092	15.118	857.023	13291.090	4.489	-0.0602	5.338	0.081	10.636	708.391	10390.080	4.519	0.0597
Brazil	26.851	0.083	5.870	492.001	19316.230	1.363	-0.0225	26.890	0.161	5.064	419.018	17606.300	1.468	0.0227
Mexico	17.859	0.080	15.800	894.757	37431.200	1.806	-0.0147	15.815	0.068	20.826	648.032	26491.190	1.764	0.0145
ISRAEL	19.889	0.026	4.393	199.824	8425.850	1.158	-0.0013	18.789	0.026	4.220	186.270	7831.980	1.146	0.0013
South Africa	22.302	0.091	3.740	256.407	10486.800	1.376	-0.0162	18.743	0.084	3.082	202.499	8295.680	1.372	0.0162
Canada	12.360	0.041	16.208	526.392	11657.320	1.800	-0.0128	10.551	0.039	15.028	430.368	9353.650	1.810	0.0129
Mean	**17.704**	**0.096**	**14.558**	**582.128**	**17056.611**	**3.818**	**-0.031**	**15.734**	**0.102**	**12.681**	**491.877**	**13891.317**	**3.993**	**0.031**

Table 3.3 (Continued)

Panel B. ETF

Country	Buy Trade Mean Price	Mean spread	Mean Depth	Mean Volume	Mean Trading Value	Mean Volatility (10^{-4})	Mean Return (10^{-2})	Sell Trade Mean Price	Mean spread	Mean Depth	Mean Volume	Mean Trading Value	Mean Volatility (10^{-4})	Mean Return (10^{-2})
Australia	10.286	0.1022	22.9024	515.894	8938.490	0.711	-0.0287	8.190	0.0888	14.5294	512.362	8772.010	0.568	0.0293
Singapore	4.461	0.0492	28.4002	685.973	5723.510	4.533	-0.0355	3.786	0.0415	23.0347	627.154	5203.920	4.517	0.0357
Japan	4.877	0.0067	302.8740	281.089	3332.820	0.267	-0.0009	4.926	0.0076	300.0270	270.071	3184.250	0.274	0.0010
China	50.271	0.1269	8.6767	174.156	15457.280	1.165	-0.0141	42.097	0.1240	4.9838	137.374	12436.680	1.131	0.0144
HongKong	6.208	0.0600	25.9577	801.381	9804.580	4.492	-0.0322	5.659	0.0636	22.1788	763.965	9270.380	4.541	0.0330
India														
Korea	20.754	0.0915	11.4237	448.905	17011.680	2.338	-0.0260	19.782	0.0913	10.3780	445.802	17024.020	2.297	0.0262
Malaysia	3.556	0.0443	41.7530	974.324	6755.520	6.532	-0.0432	3.195	0.0437	35.4529	900.894	6182.780	6.623	0.0442
Taiwan	6.003	0.0341	33.9956	694.529	8616.980	1.742	-0.0134	5.6731	0.0283	34.9588	658.248	8139.150	1.675	0.0132
Indonesia														
Philippine														
Germany	10.969	0.0761	27.6301	593.388	12007.190	3.766	-0.0230	9.481	0.0712	20.7286	545.357	10842.580	3.687	0.0230
Belgium	11.449	0.1361	24.5286	687.454	12887.660	7.410	-0.0475	8.254	0.1128	16.0502	436.561	8133.8800	6.7178	0.0429
Italy	11.394	0.1898	36.1209	1088.870	22576.920	19.029	-0.0132	9.752	0.1836	31.1491	1009.500	21095.060	19.400	0.0148
Netherlands	11.582	0.1440	27.5653	612.845	13150.510	10.529	-0.0305	9.862	0.1231	22.5355	503.280	10726.730	8.812	0.0321
Sweden	13.723	0.1537	26.8859	506.578	11555.940	8.902	-0.0345	10.482	0.1225	19.4113	395.442	9006.420	7.231	0.0337
Ireland														
Spain	23.001	0.1588	26.5555	488.161	18049.630	7.634	-0.0230	16.633	0.1281	21.6548	382.253	13528.100	5.864	0.0256
Switzerland	10.862	0.1987	34.1105	521.831	9733.490	8.702	-0.0514	8.205	0.1557	26.1085	450.242	8463.740	7.454	0.0525
France	10.983	0.255	30.810	1089.590	22626.420	17.556	-0.0460	9.397	0.245	25.470	975.782	19869.060	17.110	0.0485
UK	10.213	0.142	33.603	1111.710	19224.400	7.099	-0.0494	8.213	0.115	25.215	956.085	16414.100	6.124	0.0494
Russia														
Turkey														
Chile														
Brazil	16.951	0.078	29.296	797.742	22580.840	2.698	-0.0308	15.800	0.083	23.556	846.950	23308.040	2.611	0.0307
Mexico	18.508	0.080	9.945	506.359	16879.750	2.492	-0.0179	19.419	0.086	9.891	536.701	17792.620	2.368	0.0182
ISRAEL														
South Africa	51.132	0.271	4.186	238.381	22718.920	3.951	-0.0315	46.848	0.270	3.225	236.424	22317.890	3.634	0.0332
Canada	11.774	0.067	47.541	604.266	11517.900	3.499	-0.0154	9.559	0.054	33.601	621.718	11095.460	3.100	0.0156
Asia	55.863	0.196	9.080	297.440	27406.490	2.688	-0.0252	40.693	0.162	5.338	260.107	24007.540	2.321	0.0268
Europe	46.206	0.198	29.161	483.456	35165.310	5.252	-0.0236	30.833	0.132	17.263	387.856	27814.070	4.196	0.0241
Latin America	66.557	0.234	5.174	181.284	22091.310	2.530	-0.0188	61.212	0.213	3.295	166.848	21073.660	2.152	0.0195
EM	51.767	0.059	7.511	364.863	37174.390	0.595	-0.0057	48.263	0.065	6.356	358.567	36339.080	0.580	0.0057
Mean	**21.574**	**0.126**	**35.427**	**590.019**	**16519.517**	**5.444**	**-0.027**	**18.248**	**0.112**	**30.256**	**535.422**	**14881.649**	**5.000**	**0.028**

Table 3.3 (Continued)

Panel C. Closed-end Fund (CEF)														
	Buy Trade							Sell Trade						
Country	Mean Price	Mean spread	Mean Depth	Mean Volume	Mean Trading Value	Mean Volatility (10^{-4})	Mean Return (10^{-2})	Mean Price	Mean spread	Mean Depth	Mean Volume	Mean Trading Value	Mean Volatility (10^{-4})	Mean Return (10^{-2})
Australia	5.265	0.4212	9.0933	483.597	4483.670	0.329	-0.1822	3.968	0.1214	12.3260	442.600	3705.820	0.221	0.1757
Singapore	4.817	0.2127	5.8671	415.272	3647.880	13.075	-0.1223	4.378	0.2236	5.9397	453.061	3715.930	14.302	0.1267
Japan	3.802	0.2271	10.4470	531.408	4035.450	14.271	-0.0934	3.471	0.1782	10.2070	495.231	3757.610	14.417	0.0952
China	15.208	0.1874	2.8369	222.683	6579.240	5.019	-0.0363	14.299	0.1833	2.5634	210.514	6168.460	5.255	0.0361
HongKong														
India	35.955	0.1039	4.4749	119.411	8641.260	3.2954	-0.0385	35.400	0.1109	3.8910	116.091	8392.200	3.3381	0.0389
Korea	12.039	0.1519	5.9876	457.545	8725.320	4.185	-0.0466	11.190	0.1479	5.5790	490.917	9081.420	4.397	0.0464
Malaysia	3.497	0.1387	9.8797	483.656	3820.700	17.807	-0.1181	3.775	0.1587	11.3397	512.252	3804.120	19.709	0.1194
Taiwan	6.808	0.2452	6.2929	518.320	6663.080	6.553	-0.0892	6.383	0.2592	5.6225	510.916	6371.610	7.010	0.0912
Indonesia	3.749	0.1113	8.1789	460.168	3327.030	22.488	-0.1645	3.519	0.1176	7.5210	445.380	3060.090	23.295	0.1651
Philippine	4.643	0.0947	13.2085	487.749	4866.150	18.095	-0.1055	4.811	0.1080	14.6139	564.853	5307.950	19.384	0.1049
Germany	5.217	0.1869	15.3524	585.595	6473.210	10.916	-0.1278	5.000	0.0913	17.2128	620.636	6549.940	10.082	0.1274
Belgium														
Italy	5.337	0.1433	14.5890	729.023	9205.360	16.196	-0.1247	5.951	0.1938	18.3245	836.496	10236.420	16.804	0.1209
Netherlands														
Sweden														
Ireland	7.901	0.1756	6.8503	298.023	4431.400	14.926	-0.0746	7.250	0.1966	5.7296	317.427	4595.050	15.138	0.0754
Spain	5.213	0.1366	7.2913	398.632	5131.550	14.497	-0.1491	6.340	0.2616	12.3341	440.721	5484.620	18.288	0.1455
Switzerland	6.716	0.1772	5.1662	384.028	5193.460	7.356	-0.0879	6.868	0.2027	5.2058	460.180	6002.540	8.331	0.0838
France	4.766	0.155	20.338	735.100	8330.790	13.927	-0.1155	5.522	0.210	24.027	845.550	9330.120	15.218	0.1109
UK														
Russia	23.312	0.282	2.753	248.251	9111.820	9.962	-0.0493	20.022	0.268	2.248	224.302	8148.670	9.781	0.0499
Turkey	8.527	0.233	3.970	327.966	4736.060	9.471	-0.0725	7.731	0.227	3.602	315.335	4493.210	9.983	0.0727
Chile	10.597	0.176	6.419	398.439	7919.830	10.964	-0.0658	10.113	0.196	7.721	428.090	7909.950	11.849	0.0683
Brazil	17.016	0.246	3.877	326.201	10517.540	5.775	-0.0552	18.494	0.279	4.357	403.573	13398.560	6.874	0.0587
Mexico	6.429	0.082	17.663	542.011	9109.560	7.742	-0.0503	10.366	0.181	27.409	653.747	11259.900	9.036	0.0523
ISRAEL	7.073	0.203	5.598	378.745	5316.290	14.608	-0.0810	6.561	0.199	4.981	376.036	5147.660	14.922	0.0808
South Africa	25.046	0.172	2.360	180.691	8326.750	3.128	-0.0289	21.699	0.157	2.074	164.642	7528.910	3.147	0.0290
Canada	3.724	0.107	16.528	698.968	4435.370	6.612	-0.0727	2.793	0.038	13.117	548.554	3463.010	6.167	0.0733
Asia	7.949	0.414	5.884	460.363	5688.560	8.691	-0.0858	4.753	0.202	5.098	378.352	4227.820	6.788	0.0879
Europe	21.401	0.221	3.361	218.319	8120.040	5.332	-0.0409	18.649	0.219	2.830	212.997	7632.850	5.672	0.0422
Latin America	11.497	0.159	3.323	278.140	5512.430	7.248	-0.0584	9.959	0.167	2.845	293.482	5392.520	7.818	0.0510
EM	6.537	0.178	5.091	292.536	3815.690	5.101	-0.0513	6.307	0.173	4.836	311.596	4032.670	5.539	0.0485
Mean	**10.001**	**0.191**	**7.953**	**416.459**	**6291.625**	**9.913**	**-0.085**	**9.485**	**0.181**	**8.698**	**431.198**	**6364.273**	**10.456**	**0.085**

Table 3.4 Relative Price Ratios of the Leading ADR, ETF, and CEF, and Buyer versus Seller

For each country and region, the triplets (Leading ADR, ETF and CEF), and type of trade (buy or sell), we compute the volume-weighted average price at which trades occur, scale by the average price for every 5-minute interval and multiply by 100.. T-statistics examine whether the ratios are significantly different from 100 or differ across the investment vehicles (the Triplets). Table 8 represents the relative price ratios of the Leading ADR, ETF, and CEF for the buy trades and sell trades. ** indicates significance at 1% level and * indicates significance at 5% level.

Country		Buyer (1) Leading ADR	(2) ETF	(3) CEF	(1)Different from (2) t-statistics	(2)Different from (3) t-statistics	(1)Different from (3) t- statistics	Seller (1) Leading ADR	(2) ETF	(3) CEF	(1)Different from (2) t- statistics	(2)Different from (3) t- statistics	(1)Different from (3) t- statistics
Australia	VWA PR	100.006	100.005	100.002	-6.16**	0.78**	-0.890	99.990	99.993	99.998	0.960	-7.75**	-2.12**
	t-test:H0=100	62.55**	24.47**	4.28**				-68.41**	-26.020	-4.480			
Singapore	VWA PR	100.036	100.017	100.004	30.95**	6.26**	28.42**	99.965	99.979	99.995	-25.61**	-6.77**	-23.74**
	t-test:H0=100	72.68**	39.75**	4.84**				-70.74**	-38.58**	-5.76**			
Japan	VWA PR	100.012	100.024	100.014	-45.77**	15.3**	-4.78**	99.986	99.973	99.983	45.02**	-13.27**	-2.73**
	t-test:H0=100	123.58**	122.96**	17.3**				-125.57**	-134.07**	-17.3**			
China	VWA PR	100.010	100.012	100.016	-9.78**	-12.02**	-11.07**	99.988	99.985	99.984	10.68**	4.71**	5.7**
	t-test:H0=100	83.25**	89.67**	25.95**				-87.46**	-94.28**	-24.7**			
HongKong	VWA PR	100.048	100.018		8.65**			99.959	99.980		-7.39**		
	t-test:H0=100	16.35**	54.0**					-17.28**	-53.04**				
India	VWA PR	100.031		100.018			33.82**	99.968		99.979			-30.34**
	t-test:H0=100	78.26**		69.56**				-76.53**		-68.72**			
Korea	VWA PR	100.015	100.013	100.009	12.05**	9.66**	18.51**	99.981	99.986	99.991	-16.35**	-12.68**	-24.3**
	t-test:H0=100	106.31**	59.97**	34.75**				-111.98**	-58.48**	-30.61**			
Malaysia	VWA PR		100.021	100.016		6.57**			99.978	99.985		-5.64**	
	t-test:H0=100		32.45**	11.38**					-32.85**	-11.68**			
Taiwan	VWA PR	100.029	100.018	100.006	20.43**	8.24**	28.19**	99.966	99.981	99.993	-27.17**	-7.07**	-28.46**
	t-test:H0=100	141.26**	70.99**	10.3**				-146.18**	-72.95**	-10.36**			
Indonesia	VWA PR	100.028		100.018			20.41**	99.973		99.979			-21.5**
	t-test:H0=100	58.53**		9.91**				-56.55**		-10.4**			
Philippine	VWA PR	100.008		100.015			-6.69**	99.991		99.985			5.27**
	t-test:H0=100	18.28**		12.34**				-17.13**		-11.52**			
Germany	VWA PR	100.019	100.010	100.009	24.84**	-2.77*	14.65**	99.979	99.988	99.991	-16.08**	-0.960	-11.34**
	t-test:H0=100	107.32**	47.35**	15.23**				-114.22**	-48.59**	-15.74**			
Belgium	VWA PR	100.005	100.006		-1.94*			99.997	99.992		6.22**		
	t-test:H0=100	14.43**	11.84**					-12.71**	-14.37**				
Italy	VWA PR	100.005	100.002	100.007	0.730	-3.12**	-2.53*	99.993	99.998	99.997	-1.86*	1.87*	0.690
	t-test:H0=100	21.11**	3.69**	4.76**				-20.52**	-2.94*	-4.04**			
Netherlands	VWA PR	100.018	100.005		23.26**			99.979	99.994		-26.53**		
	t-test:H0=100	119.63**	13.32**					-124.36**	-12.05**				
Sweden	VWA PR	100.084	100.008		96.3**			99.912	99.990		-108.68**		
	t-test:H0=100	229.98**	21.79**					-223.96**	-21.46**				

Table 3.4 (Continued)

Country		Buyer (1) Leading ADR	(2) ETF	(3) CEF	(1)Different from (2) t-statistics	(2)Different from (3) t-statistics	(1)Different from (3) t- statistics	Seller (1) Leading ADR	(2) ETF	(3) CEF	(1)Different from (2) t- statistics	(2)Different from (3) t- statistics	(1)Different from (3) t- statistics
Ireland	VWA PR	100.040		100.007			9.87**	99.955		99.993			-13.78**
	t-test:H0=100	148.87**		10.66**				-160.12**		-10.22**			
Spain	VWA PR	100.010	100.005	100.007	5.4**	-2.78**	0.58**	99.989	99.993	99.995	3.74**	-1.76*	-0.190
	t-test:H0=100	73.73**	20.13**	5.69**				-77.65**	-17.17**	-5.37**			
Switzerland	VWA PR	100.010	100.006	100.004	8.51**	2.68**	9.38**	99.987	99.992	99.996	-9.76**	-5.2**	-21.46**
	t-test:H0=100	110.14**	13.78**	8.97**				-124.59**	-9.91**	-9.54**			
France	VWA PR	100.030	100.001	100.007	11.13**	-4.74**	5.01**	99.963	99.997	99.996	-10.03**	2.34**	-15.37**
	t-test:H0=100	92.33**	3.34**	5.84**				-97.15**	-3.74**	-7.03**			
UK	VWA PR	100.021	100.007		25.46**			99.977	99.991		-7.01**		
	t-test:H0=100	152.38**	27.16**					-163.81**	-27.39**				
Russia	VWA PR	100.017		100.019			6.22**	99.981		99.979			-7.45**
	t-test:H0=100	50.89**		28.5**				-54.99**		-25.53**			
Turkey	VWA PR	100.014		100.016			-5.61**	99.980		99.984			2.65**
	t-test:H0=100	43.07**		18.84**				-47.37**		-18.21**			
Chile	VWA PR	100.012		100.013			-6.4**	99.986		99.990			1.16*
	t-test:H0=100	38.37**		18.3**				-30.64**		-18.37**			
Brazil	VWA PR	100.014	100.018	100.007	0.31	8.42**	9.78**	99.984	99.981	99.993	-8.24**	-13.98**	-16.89**
	t-test:H0=100	77.01**	58.66**	15.29**				-79.65**	-61.78**	-16.35**			
Mexico	VWA PR	100.016	100.012	100.026	35.17**	-19.41**	8.47**	99.979	99.988	99.983	-42.28**	16.93**	-29.06**
	t-test:H0=100	122.52**	50.7**	36.68**				-134.92**	-50.07**	-39.3**			
ISRAEL	VWA PR	100.032		100.008			32.56**	99.968		99.994			-38.45**
	t-test:H0=100	142.67**		10.42**				-146.32**		-8.36**			
South Africa	VWA PR	100.014	100.010	100.013	15.27**	-11.01**	9.56**	99.983	99.990	99.986	-19.16**	10.14**	-17.15**
	t-test:H0=100	101.85**	25.3**	48.02**				-105.94**	-23.31**	-45.2**			
Canada	VWA PR	100.033	100.015	100.018	61.64**	-0.130	59.57**	99.964	99.981	99.977	-48.14**	4.01**	-43.46**
	t-test:H0=100	175.32**	61.49**	45.74**				-187.15**	-59.45**	-45.68**			
Asia	VWA PR		100.007	100.005		1.19			99.991	99.991		1.11	
	t-test:H0=100		48.91**	12.54**					-48.04**	-13.18**			
Europe	VWA PR		100.006	100.014		-19.17**			99.991	99.985		11.44**	
	t-test:H0=100		36.7**	30.43**					-34.99**	-30.78**			
LatinAmerica	VWA PR		100.013	100.006		-2.11*			99.985	99.992		-1.68*	
	t-test:H0=100		58.18**	11.43**					-59.54**	-7.0**			
EM	VWA PR		100.010	100.017		-17.52**			99.989	99.984		10.4**	
	t-test:H0=100		97.26**	38.61**					-101.57**	-39.37**			
Mean		**100.022**	**100.011**	**100.012**				**99.976**	**99.988**	**99.989**			

Table 3.5 Leads and Lags and Granger Causality Test of the returns among the Triplets (Leading ADR, ETF and CEF)

Table 5 presents the results of the VAR on the returns of the leading ADR, ETF, and CEF across the countries. And $\chi^2(6)$ show the results of the Granger Causality test for the relations of the returns of the leading ADR, ETF, and CEF. It only presents the coefficients of the returns of one security on the lag returns of the other two for last period and the past 6th period. ** indicates significance at 1% level and * indicates significance at 5% level.

Country	Leading ADR						ETF					
	ETF			CEF			Leading ADR			CEF		
	P=1	P=6	$\chi^2(6)$	P=1	P=6	$\chi^2(6)$	P=1	P=6	$\chi^2(6)$	P=1	P=6	$\chi^2(6)$
Australia	0.030	0.013	99.45**	0.014	0.008	116.82**	0.011	0.004	237.82**	0.002	0.006	65.48**
Singapore	0.015	0.013	12.28	0.006	-0.001	20.11*	-0.001	0.001	41.04**	0.007	0.002	31.17**
Japan	0.038	0.016	111.95**	0.022	-0.004	144.15**	0.013	0.003	341.51**	0.036	0.022	290.55**
China	0.006	-0.001	3.81	0.021	-0.012	11.38	0.0003	-0.0001	6.57	0.008	0.012	10.53
HongKong	0.002	0.003	35.37**				0.016	-0.0003	10.29			
India	0.011	0.002	10.32				0.008	-0.003	44.36**			
Korea	0.057	0.020	176.53**	0.045	0.012	194.43**	0.005	-0.003	262.95**	0.016	-0.004	194.43**
Malaysia	0.013	0.005	83.89**				0.026	0.002	39.33**			
Taiwan	0.016	0.060	74.320	0.029	0.021	207.11**	0.002	0.000	321.67**	0.027	0.008	315.71**
Indonesia	0.004	0.005	29.41**				0.006	-0.001	20.87**			
Philippine	0.034	0.020	201.87**				0.019	0.003	87.8**			
Germany	0.058	0.014	106.61**	0.036	0.002	196.4**	0.009	0.000	196.4**	0.021	0.004	124.49**
Belgium	0.016	0.018	15.91**				0.004	0.005	29.18**			
Italy	0.050	0.022	98.87**	0.022	0.003	157.43**	0.015	0.004	308.96**	0.017	0.011	119.25**
Netherlands	0.038	0.024	17.49**				0.003	0.001	129.6**			
Sweden	0.011	0.017	12.50*				0.00002	-0.001	5.21			
Ireland	0.012	0.013	14.25**				0.003	-0.002	29.86**			
Spain	0.044	0.006	80.21**	0.030	0.003	79.06**	0.014	0.001	107.37**	0.007	0.005	79.06**
Switzerland	0.027	-0.001	19.92*	0.014	0.012	29.88**	0.002	0.000	92.64**	0.006	0.005	59.48**
France	0.014	0.004	41.53**	0.015	0.003	59.39**	0.002	-0.001	64.91**	0.008	0.0001	42.34**
UK	0.052	0.030	31.12**				0.004	0.002	158.92**			
Russia	0.052	0.006	222.79**				0.018	0.006	241.19**			
Turkey	0.028	0.001	31.19**				0.017	-0.001	172.15**			
Chile	0.024	0.006	79.37**				0.012	0.005	127.40**			
Brazil	0.063	0.034	88.8**	0.049	0.012	241.61**	0.006	-0.001	402.61**	0.017	0.008	114.96**
Mexico	0.013	0.013	19.05**	0.017	0.005	142.61**	0.003	0.0004	86.64**	0.009	0.004	179.72**
ISRAEL	-0.001	0.002	26.51**				-0.003	-0.002	14.38**			
South Africa	0.042	0.015	8.96	0.059	0.010	22.04*	0.002	0.001	123.28**	0.005	0.001	77.12**
Canada	-0.004	0.007	12.93	0.024	0.005	23.46*	-0.001	0.0002	17.57	-0.005	-0.003	14.45
Asia	0.011	-0.006	15.02**				0.009	0.003	15.47**			
Europe	0.014	0.018	48.00**				0.020	0.014	73.89**			
LatinAmerica	0.073	0.032	237.76**				0.029	0.008	380.09**			
EM	-0.00571	0.00836	2.15				-0.00042	0.00066	2.82			
Mean	**0.026**	**0.013**		**0.027**	**0.005**		**0.008**	**0.002**		**0.012**	**0.005**	

Table 3.6 Leads and Lags and Granger Causality Test of the volumes among the Triplets (Leading ADR, ETF and CEF)

Table 6 presents the results of the VAR on the volumes of the leading ADR, ETF, and CEF across the countries. And $\chi^2(6)$ show the results of the Granger Causality test for the relations of the volumes of the leading ADR, ETF, and CEF. It only presents the coefficients of the volumes of one security on the lag returns of the other two for last period and the past 6th period. ** indicates significance at 1% level and * indicates significance at 5% level.

Country	Leading ADR						ETF					
	ETF			CEF			Leading ADR			CEF		
	P=1	P=6	$\chi^2(6)$	P=1	P=6	$\chi^2(6)$	P=1	P=6	$\chi^2(6)$	P=1	P=6	$\chi^2(6)$
Australia	-0.0006	0.00004	3.55	-0.0009	-0.0008	1.28	0.0039	0.0004	1.37	-0.0005	-0.0005	0.59
Singapore	-0.0112	-0.0135	16.64*	-0.0011	0.0028	5.14	-0.0014	-0.0014	22.44*	0.0002	-0.0001	13.31
Japan	0.0377	0.0807	27.47**	0.0006	0.0013	10.8*	0.0001	0.0002	33.53**	0.0001	-0.0001	40.47**
China	0.0078	0.0003	2.79	0.0064	0.0068	9.61	0.0009	0.0005	10.83	0.0062	0.0029	12.61
HongKong	-0.0047	-0.0034	3.12				-0.0018	-0.0012	3.55			
India	-0.0024	0.0002	1.41				0.0355	0.0089	0.94			
Korea	0.0018	-0.0075	55.69**	0.0093	0.0091	48.71**	0.0019	-0.0011	70.23**	-0.0017	-0.0034	13.65
Malaysia	0.0001	-0.0006	1.90				-0.0244	-0.0035	3.42			
Taiwan	0.0149	-0.0013	14.11	0.0036	0.0028	15.35	0.0007	0.0003	19.09*	-0.0001	-0.0001	8.50
Indonesia	0.0002	0.0004	32.32**				-0.0281	-0.0012	6.78			
Philippine	0.0002	-0.0003	3.66				-0.0048	-0.0007	4.88			
Germany	-0.0036	-0.0020	32.91**	0.0015	0.0022	31.24**	-0.0006	-0.0012	6.91	-0.0003	-0.0009	5.51
Belgium	-0.0351	-0.0478	0.90				-0.0001	-0.0001	0.79			
Italy	-0.0011	0.00001	15.27	0.0005	0.0008	50.78**	-0.0087	-0.0007	66.74**	0.0025	0.0169	101.6**
Netherlands	-0.0015	-0.0014	17.63**				-0.0028	-0.0043	15.62**			
Sweden	-0.0034	-0.0020	10.84*				-0.0024	-0.0031	21.67**			
Ireland	-0.0007	0.0001	8.36				-0.0222	-0.0088	11.81*			
Spain	-0.0009	-0.0006	6.55	-0.00005	0.0001	8.51	-0.0009	0.0008	3.36	-0.0005	-0.0007	6.28
Switzerland	-0.0003	-0.0024	41.40**	0.0014	0.0012	41.67**	-0.0015	-0.0021	27.45**	-0.0003	0.0001	4.77
France	-0.0004	0.0007	4.91	0.0008	0.0005	3.06	-0.0019	0.0034	10.15	0.0029	-0.0004	7.85
UK	-0.0004	-0.0002	3.60				0.0006	-0.0009	4.10			
Russia	0.0020	0.0037	118.58**				0.0300	0.0215	97.09**			
Turkey	-0.0003	0.0016	11.76*				-0.0010	0.0320	25.03**			
Chile	0.0001	0.0002	1.60				-0.0019	0.0096	4.15			
Brazil	-0.0029	-0.0012	2.1000	0.0002	0.0000	9.3000	-0.0015	-0.0009	1.3800	0.0000	0.0001	1.900
Mexico	-0.0061	-0.0098	139.71**	0.0072	0.0081	95.86**	-0.0043	-0.0047	170.34**	-0.0035	-0.0026	39.13**
ISRAEL	0.0013	0.0031	23.35**				0.0056	0.0071	36.85**			
South Africa	-0.0244	-0.0127	76.2**	0.0064	0.0045	72.21**	-0.0003	-0.0007	91.21**	0.0000	-0.0005	12.08
Canada	-0.0153	-0.0178	479.11**	-0.0089	-0.0076	484.76**	-0.0006	-0.0006	518.94**	0.0002	0.0002	37.38**
Asia	-0.0014	0.0013	1.44				-0.0026	0.0037	7.93			
Europe	-0.0002	-0.0002	1.67				-0.0277	-0.0130	2.88			
LatinAmerica	-0.0060	-0.0090	88.00**				-0.0004	-0.0039	2.46			
EM	-0.000006	-0.00012	4.61				-0.0502	-0.0134	4.19			
Mean	**-0.0017**	**-0.0013**		**0.0018**	**0.0021**		**-0.0034**	**0.0006**		**0.0003**	**0.0007**	

Table 3.7 Leads and Lags and Granger Causality Test of the Volatility among the Triplets (Leading ADR, ETF and CEF)

Table 7 presents the results of the VAR on the volatilities of the leading ADR, ETF, and CEF across the countries. And $\chi^2(6)$ show the results of the Granger Causality test for the relations of the volatilities of the leading ADR, ETF, and CEF. It only presents the coefficients of the volatilities of one security on the lag returns of the other two for last period and the past 6th period. ** indicates significance at 1% level and * indicates significance at 5% level.

Country	Leading ADR						ETF					
	ETF			CEF			Leading ADR			CEF		
	P=1	P=6	$\chi^2(6)$	P=1	P=6	$\chi^2(6)$	P=1	P=6	$\chi^2(6)$	P=1	P=6	$\chi^2(6)$
Australia	0.0905	0.0495	1185.46**	0.0319	0.0376	1081.48**	0.0235	0.0081	1127.84**	0.0109	0.0028	548.41**
Singapore	0.0229	0.0161	180.37**	0.0164	0.0076	41.98**	0.0101	0.0071	216.02**	0.0041	-0.0001	201.12**
Japan	0.0477	0.0387	1871.34**	0.0392	0.0230	315.72**	0.0253	0.0114	978.21**	0.0335	0.0047	1037.37**
China	0.0150	-0.0004	11.09	0.0001	0.0010	23.16**	0.0012	-0.0008	8.04	0.0092	0.0020	19.99*
HongKong	0.0199	0.0083	269.18**				0.0277	0.0223	342.21**			
India	0.0350	0.0035	355.79**				0.0240	0.0299	742.88**			
Korea	0.0584	-0.0030	602.39**	0.0687	0.0302	560.66**	0.0085	0.0033	647.09**	0.0099	0.0064	174.64**
Malaysia	0.0285	0.0250	828.13**				0.0468	0.0345	1044.47**			
Taiwan	0.0399	0.1998	178.58**	0.0718	-0.0003	246.89**	0.0034	0.0005	848.16**	0.0186	0.0037	654.56**
Indonesia	0.0172	0.0115	195.39**				0.0150	0.0060	201.19**			
Philippine	0.0151	0.0172	310.27**				0.0248	-0.0003	21.9**			
Germany	0.0475	0.0125	678.54**	0.0535	0.0263	674.63**	0.0095	0.0032	1193.41**	0.0185	0.0087	478.17**
Belgium	0.0146	0.0030	21.82**				0.0080	0.0020	20.70**			
Italy	0.0501	0.0130	205.32**	0.0183	-0.0103	187.52**	0.0223	0.0017	262.00**	0.0127	0.0090	309.86**
Netherlands	0.0252	-0.0033	18.75**				0.0026	-0.0022	39.84**			
Sweden	0.0008	-0.0076	28.26**				0.0008	-0.0003	40.32**			
Ireland	0.0245	0.0147	262.8**				0.0124	0.0055	196.76**			
Spain	0.0406	0.0004	268.71**	0.0377	0.0110	182.62**	0.0164	0.0027	447.81**	0.0119	0.0019	338.11**
Switzerland	0.0168	0.0006	58.92**	0.0358	0.0063	90.59**	0.0032	0.0001	177.33**	0.0046	0.0028	74.46**
France	0.0002	0.0010	192.36**	0.0151	0.0115	211.14**	0.0016	0.0025	321.04**	0.0027	0.0014	27.14**
UK	0.0309	-0.0086	42.37**				0.0053	0.0020	84.18**			
Russia	0.0597	0.0379	1158.71**				0.0284	0.0138	1515.26**			
Turkey	0.0230	0.0027	221.02**				0.0600	0.0043	168.38**			
Chile	0.0195	0.0097	228.02**				0.0224	0.0003	106.97**			
Brazil	0.0379	0.0083	88.39**	0.0311	-0.0020	123.71**	0.0007	0.0011	156.37**	0.0150	0.0014	169.79**
Mexico	0.0083	0.0116	1909.88**	0.0593	0.0469	1948.43**	0.0045	0.0008	1540.36**	0.0101	0.0026	183.54**
ISRAEL	0.0149	0.0213	842.92**				0.0244	0.0227	1253.68**			
South Africa	-0.0175	-0.0482	101.98**	0.0238	0.0118	74.03**	-0.0018	-0.0011	109.32**	0.0020	-0.0018	43.30**
Canada	-0.0173	-0.0162	110.90**	0.0121	-0.0020	51.18**	-0.0032	-0.0042	386.87**	0.0033	0.0057	415.12**
Asia	0.0165	0.0079	45.79**				0.0132	0.0018	39.98**			
Europe	0.0243	0.0074	78.70**				0.0243	0.0090	66.34**			
LatinAmerica	0.0699	0.0236	618.27**				0.0426	0.0193	481.27**			
EM	0.02825	0.00858	76.43**				0.00843	0.00335	68.01**			
Mean	**0.0275**	**0.0141**		**0.0343**	**0.0132**		**0.0156**	**0.0064**		**0.0111**	**0.0034**	

Table 3.8 Leads and Lags and Granger Causality Test of the Quoted Spreads among the Triplets (Leading ADR, ETF,CEF)

Table 8 presents the results of the VAR on the quoted spreads of the leading ADR, ETF, and CEF across the countries. And $\chi^2(6)$ show the results of the Granger Causality test for the relations of the quoted spreads of the leading ADR, ETF, and CEF. It only presents the coefficients of the quoted spreads of one security on the lag returns of the other two for last period and the past 6th period. ** indicates significance at 1% level and * indicates significance at 5% level.

Country	Leading ADR						ETF					
	ETF			CEF			Leading ADR			CEF		
	P=1	P=6	$\chi^2(6)$	P=1	P=6	$\chi^2(6)$	P=1	P=6	$\chi^2(6)$	P=1	P=6	$\chi^2(6)$
Australia	0.1523	0.0584	276.43**	0.0242	0.0173	350.29**	0.0011	0.0012	265.8**	0.0102	0.0053	81.26**
Singapore	0.0038	0.0233	106.03**	0.0068	-0.0034	380.49**	0.0043	0.0027	115.34**	0.0221	0.0243	466.18**
Japan	0.0031	0.0021	119.79**	-0.0009	-0.0030	66.07**	0.0412	0.0123	113.78**	0.0017	-0.0119	157.05**
China	0.0070	0.0021	116.72**	0.0044	0.0008	83.39**	0.0305	0.0139	73.34**	0.0201	0.0132	111.18**
HongKong	0.0163	-0.0056	8.62				-0.0003	-0.0015	9.92			
India	-0.0002	-0.0026	24.2**				-0.0024	-0.0070	99.51**			
Korea	0.0186	0.0028	201.3**	0.0054	0.0010	88.82**	0.0203	0.0100	208.31**	0.0069	0.0061	245.3**
Malaysia	0.0156	0.0078	335.03**				0.0269	0.0013	288.92**			
Taiwan	0.0041	0.0010	20.91*	0.0131	-0.0069	274.48**	0.0039	-0.0019	28.39**	0.0205	0.0154	274.19**
Indonesia	0.0024	0.0014	45.13**				0.0392	-0.0040	19.89**			
Philippine	0.0067	0.0051	302.84**				0.0572	0.0389	248.43**			
Germany	0.0111	0.0050	159.22**	0.0010	-0.0043	61.99**	0.0053	0.0065	314.98**	0.0081	-0.0015	272.1**
Belgium	-0.0004	0.0053	29.21**				0.0120	0.0204	20.13**			
Italy	0.0065	0.0041	151.14**	-0.0003	-0.0004	56.38**	0.0392	0.0206	173.53**	0.0198	0.0010	214.54**
Netherlands	0.0014	0.0015	53.95**				0.0143	-0.0048	58.22**			
Sweden	0.0053	-0.0101	31.65**				0.0013	-0.0002	31.12**			
Ireland	0.0021	0.0014	25.76**				0.0103	0.0019	11.95*			
Spain	-0.0018	-0.0020	49.92**	0.0050	-0.0013	85.92**	-0.0008	-0.0042	70.04**	0.0123	0.0092	64.43**
Switzerland	0.0033	-0.0045	18.51*	-0.0020	-0.0058	64.33**	0.0099	0.0063	31.68**	0.0136	0.0085	70.27**
France	0.0030	-0.0017	47.88**	0.0055	0.0021	136.66**	0.0063	0.0006	51.56**	0.0163	0.0052	118.62**
UK	0.0048	0.0058	56.70**				0.0123	0.0021	51.74**			
Russia	0.0045	0.0025	65.01**				0.0119	0.0083	40.93**			
Turkey	0.0201	0.0120	432.35**				0.0360	0.0222	503.84**			
Chile	-0.0017	-0.0047	6.47**				0.0027	0.0010	4.87**			
Brazil	0.0102	0.0057	444.88**	0.0111	0.0163	406.79**	0.0354	0.0135	369.01**	0.0189	0.0088	410.22**
Mexico	0.0132	0.0049	185.24**	0.0024	-0.0018	80.23**	0.0152	0.0149	310.39**	0.0069	-0.0007	340.52**
ISRAEL	-0.0010	-0.0002	45.17**				0.0001	0.0038	39.77**			
South Africa	-0.0058	-0.0018	109.76**	0.0081	0.0035	118.03**	-0.0093	-0.0038	81.08**	0.0124	0.0058	66.93**
Canada	0.0043	-0.0007	246.90**	0.0086	0.0020	1245.52**	0.0075	0.0024	249.15**	0.0149	0.0106	1313.42**
Asia	0.0104	0.0148	61.78**				0.0176	-0.0027	36.89**			
Europe	0.0057	0.0004	28.06**				0.0136	0.0015	13.93**			
LatinAmerica	-0.0028	0.0005	23.38**				0.0193	-0.0139	14.50**			
EM	0.01381	0.00628	138.32**				0.0201	0.01383	95.96**			
Mean	**0.0102**	**0.0043**		**0.0061**	**0.0011**		**0.0152**	**0.0053**		**0.0136**	**0.0066**	

Table 3.9 Explaining the Price-setting Buy-Sell Imbalance and Short-Horizon Returns

This table presents the results of VAR model on the net order imbalances and short-horizon returns. I define the price-setting buys and sells by using the algorithm developed by Lee and Ready (1991). For each 5 minute interval for all the three securities across the countries, I compute "price-setting" order imbalances by security type by subtracting the price-setting sell volume from the price-setting buy volume, and then normalizing by the stock's average 5-minute price-setting volume over the sample period. Vector Y_t can be expressed in terms of current and lagged innovations: $Y_t=A_t+\sum A_j Y_{t-j}+u_t$, where $Y_t=\{OIB_t^1, OIB_t^2, OIB_t^3, R_t^1, R_t^2, R_t^3\}$ represents net order imbalances and returns of the leading ADR, ETF, and CEF respectively. The lag length is chosen as k=6 by Akaike and Schwartz-Bayes criteria. Panel A-F show the average coefficients of the VARs across all the countries when the dependent variables are OIBADR, OIBETF, OIBCEF, ReturnADR, ReturnETF, and ReturnCEF. Panel A summarizes the results of VARs on order flows and returns. Panel B-E also summarizes the coefficients of VARs in the regions of Asia and Pacific, Europe, Latin America, and Emerging Market respectively. Dependent variables are denoted by 1-6. 1 is OIBADR; 2 is OIBETF; 3 is OIBCEF; 4 is ReturnADR; 5 is ReturnETF; 6 is ReturnCEF;

		Panel A					
	Lag	1	2	3	4	5	6
OibADR	1	0.1533	0.0042	0.0061	0.3347	0.0133	0.0183
	2	0.0669	0.0028	0.0041	0.0772	0.0055	0.0110
	3	0.0525	0.0026	0.0027	0.0163	0.0135	0.0053
	4	0.0449	0.0022	0.0022	-0.0050	0.0004	0.0085
	5	0.0396	0.0017	0.0020	-0.0120	0.0100	0.0067
	6	0.0414	0.0036	0.0021	-0.0283	0.0024	0.0108
OibETF	1	0.0043	0.1573	0.0080	0.0108	0.2403	0.0248
	2	0.0037	0.0773	0.0062	0.0034	0.0772	0.0273
	3	0.0019	0.0583	0.0063	0.0027	0.0354	0.0150
	4	0.0036	0.0481	0.0029	-0.0062	0.0147	0.0181
	5	0.0031	0.0426	0.0036	0.0014	0.0071	0.0062
	6	0.0026	0.0459	0.0051	0.0067	0.0023	-0.0047
OibCEF	1	0.0073	0.0103	0.1444	0.0171	0.0130	0.4102
	2	0.0026	0.0075	0.0686	0.0006	0.0097	0.1982
	3	0.0046	0.0045	0.0467	0.0086	0.0083	0.1171
	4	0.0066	0.0056	0.0398	-0.0092	0.0046	0.0951
	5	0.0027	0.0067	0.0368	-0.0005	-0.0013	0.0560
	6	0.0057	0.0075	0.0352	-0.0103	-0.0001	0.0734
ReturnADR	1	0.4616	1.3667	1.6496	-0.1856	0.0103	0.0147
	2	0.8587	0.9914	1.4500	-0.0654	0.0113	0.0139
	3	1.3044	0.1782	1.1159	-0.0310	0.0107	0.0177
	4	1.0692	0.5584	0.7099	-0.0128	0.0106	0.0124
	5	0.7346	0.2581	0.8568	-0.0077	0.0080	0.0063
	6	1.4635	-0.1333	0.7278	-0.0047	0.0054	0.0063
ReturnETF	1	0.1724	1.2594	0.2483	0.0060	-0.1157	0.0112
	2	0.2588	1.1127	0.3553	0.0046	-0.0641	0.0162
	3	0.2647	0.9783	0.3780	0.0042	-0.0411	0.0128
	4	0.1341	0.9419	0.6550	-0.0003	-0.0259	0.0136
	5	0.1520	1.1554	0.3814	0.0005	-0.0196	0.0071
	6	0.3444	1.5092	0.6978	0.0008	-0.0125	0.0066
ReturnCEF	1	0.2176	0.3304	1.0980	0.0037	0.0051	-0.1385
	2	0.1878	0.3541	0.8153	0.0028	0.0050	-0.0935
	3	0.1600	0.2586	0.7703	0.0031	0.0050	-0.0681
	4	0.2230	0.2922	0.7522	0.0025	0.0048	-0.0489
	5	0.2028	0.2694	0.7352	0.0003	0.0025	-0.0369
	6	0.1901	0.2995	0.7681	0.0012	0.0017	-0.0272

Table 3.9 (Continued)

		Panel B						Panel C					
	Lag	1	2	3	4	5	6	1	2	3	4	5	6
OibADR	1	0.1602	0.0054	0.0035	0.1395	0.0289	0.0146	0.1503	0.0019	0.0030	0.2975	-0.0002	0.0133
	2	0.0677	0.0057	0.0039	0.0447	-0.0041	-0.0003	0.0658	0.0012	0.0022	0.0461	0.0043	-0.0008
	3	0.0530	0.0033	0.0022	0.0110	0.0061	0.0082	0.0509	0.0004	0.0019	-0.0003	0.0232	0.0172
	4	0.0456	0.0048	0.0017	-0.0145	0.0170	0.0165	0.0434	0.0015	0.0015	-0.0180	-0.0129	0.0050
	5	0.0368	0.0068	0.0020	-0.0276	0.0027	0.0115	0.0406	-0.0005	0.0010	-0.0143	0.0151	-0.0083
	6	0.0417	0.1693	0.0007	0.0127	0.0137	0.0221	0.0398	0.0023	0.0021	-0.0319	-0.0096	0.0075
OibETF	1	0.0069	0.0769	0.0101	0.0004	0.3188	0.0124	0.0024	0.1387	0.0045	0.0137	0.1994	0.0577
	2	0.0057	0.0579	0.0052	0.0062	0.0896	-0.0067	0.0033	0.0763	0.0037	0.0078	0.0805	0.0420
	3	0.0043	0.0456	0.0071	-0.0196	0.0388	0.0363	-0.0005	0.0547	0.0059	0.0001	0.0372	0.0272
	4	0.0061	0.0436	0.0035	-0.0011	0.0108	0.0059	0.0016	0.0457	0.0018	-0.0001	0.0179	-0.0009
	5	0.0043	0.0462	0.0071	0.0036	0.0001	0.0096	0.0013	0.0384	-0.0014	0.0029	0.0172	-0.0154
	6	0.0050	0.0144	0.0062	0.0084	-0.0054	0.4647	0.0014	0.0434	0.0019	0.0130	0.0111	-0.0123
OibCEF	1	0.0057	0.0108	0.1534	-0.0114	0.0103	0.2209	0.0082	0.0050	0.1316	0.0330	0.0196	0.4110
	2	0.0020	0.0061	0.0725	-0.0016	0.0043	0.1386	0.0021	0.0045	0.0643	0.0046	0.0189	0.2068
	3	0.0024	0.0088	0.0504	-0.0088	0.0202	0.1050	0.0060	0.0022	0.0433	0.0189	-0.0070	0.1203
	4	0.0061	0.0100	0.0420	-0.0036	0.0061	0.0627	0.0069	0.0028	0.0388	-0.0123	0.0058	0.1140
	5	0.0008	0.0106	0.0399	-0.0278	-0.0186	0.0942	0.0004	0.0045	0.0363	-0.0070	0.0194	0.0650
	6	0.0028	2.3630	0.0370	-0.2136	0.0082	0.0094	0.0067	0.0029	0.0338	0.0012	-0.0024	0.0712
ReturnADR	1	1.2661	1.2895	0.9072	-0.0880	0.0085	0.0050	-0.4740	0.1645	0.0953	-0.1565	0.0118	0.0127
	2	1.6798	-0.5944	0.9559	-0.0397	0.0120	0.0163	-1.2072	0.3911	0.0033	-0.0474	0.0091	0.0143
	3	1.6050	1.4784	0.7928	-0.0134	0.0104	0.0100	0.1759	0.0833	0.1320	-0.0240	0.0104	0.0121
	4	1.3392	0.1620	0.8917	-0.0093	0.0070	-0.0007	0.5323	-0.0527	0.2534	-0.0135	0.0126	0.0089
	5	0.4666	-0.8442	0.6211	-0.0097	0.0038	0.0021	0.2749	0.0187	0.2592	-0.0064	0.0104	0.0068
	6	0.4271	0.3941	0.6552	0.0090	0.0018	0.0080	1.2098	0.2992	0.2074	-0.0009	0.0059	0.0064
ReturnETF	1	0.4998	1.0670	0.3848	0.0080	-0.1741	0.0120	0.1177	1.1732	0.1874	0.0055	-0.0688	0.0173
	2	0.2328	0.2123	0.6771	0.0087	-0.0998	0.0101	0.0988	0.9757	0.3221	0.0036	-0.0418	0.0195
	3	0.3947	0.3027	0.1001	0.0004	-0.0621	0.0071	0.2298	0.8456	0.2356	0.0025	-0.0287	0.0120
	4	0.0739	1.1688	0.7039	0.0008	-0.0370	0.0031	0.1349	0.5490	0.2187	-0.0009	-0.0204	0.0139
	5	-0.0114	1.3760	0.3062	0.0022	-0.0266	0.0064	0.3844	0.6732	-0.0491	0.0002	-0.0163	0.0128
	6	0.5660	0.3659	0.6829	0.0035	-0.0164	-0.1502	0.1167	0.7412	0.0475	0.0002	-0.0117	0.0088

Table 3.9 (Continued)

		Panel D						Panel E					
	Lag	1	2	3	4	5	6	1	2	3	4	5	6
OibADR	1	0.1498	0.0019	0.0079	0.2666	0.0249	0.0357	0.1572	0.0057	0.0086	0.4296	0.0236	0.0276
	2	0.0745	0.0025	0.0045	0.0675	0.0408	0.0165	0.0706	0.0040	0.0055	0.1163	0.0146	0.0158
	3	0.0611	0.0026	0.0026	0.0010	-0.0013	-0.0084	0.0556	0.0038	0.0041	0.0456	-0.0013	0.0057
	4	0.0516	0.0007	0.0041	-0.0095	0.0037	0.0032	0.0485	0.0020	0.0024	-0.0014	0.0096	0.0073
	5	0.0480	0.0012	0.0028	-0.0018	0.0163	0.0153	0.0404	0.0030	0.0021	-0.0096	0.0085	0.0194
	6	0.0494	0.0011	0.0041	-0.0344	0.0170	0.0094	0.0438	0.0044	0.0025	-0.0397	0.0103	0.0088
OibETF	1	0.0088	0.1578	0.0076	0.0046	0.2322	0.0394	0.0059	0.1548	0.0098	0.0137	0.2869	0.0184
	2	-0.0019	0.0794	0.0101	-0.0021	0.0570	0.0668	0.0022	0.0743	0.0079	-0.0009	0.0903	0.0179
	3	-0.0008	0.0605	0.0052	0.0003	0.0347	0.0341	0.0019	0.0568	0.0060	0.0140	0.0396	0.0184
	4	0.0025	0.0525	0.0029	0.0017	0.0125	0.0322	0.0048	0.0471	0.0045	-0.0140	0.0152	0.0115
	5	0.0063	0.0482	0.0042	0.0017	-0.0022	0.0223	0.0023	0.0427	0.0057	0.0057	-0.0009	0.0116
	6	-0.0003	0.0492	0.0083	-0.0037	-0.0043	-0.0185	0.0024	0.0460	0.0069	0.0040	-0.0041	-0.0001
OibCEF	1	0.0078	0.0154	0.1478	0.0005	0.0286	0.3482	0.0076	0.0109	0.1527	0.0100	0.0237	0.4143
	2	0.0032	0.0074	0.0714	0.0142	0.0058	0.1771	0.0024	0.0089	0.0703	0.0083	-0.0043	0.1932
	3	0.0041	0.0088	0.0454	0.0114	0.0210	0.1088	0.0033	0.0035	0.0485	0.0136	0.0175	0.1213
	4	0.0057	0.0039	0.0379	0.0091	0.0104	0.0595	0.0045	0.0059	0.0404	-0.0106	0.0055	0.0841
	5	0.0047	0.0061	0.0334	0.0087	0.0055	0.0372	0.0033	0.0051	0.0368	0.0055	-0.0077	0.0418
	6	0.0071	0.0101	0.0355	0.0009	-0.0251	0.0450	0.0051	0.0079	0.0350	-0.0130	0.0004	0.0868
ReturnADR	1	-0.9496	1.3060	2.8440	-0.2555	0.0055	0.0275	1.6311	3.1641	2.9291	-0.2130	0.0092	0.0177
	2	1.0588	1.2435	2.3739	-0.0905	0.0134	0.0298	2.4751	1.6572	2.3950	-0.0818	0.0152	0.0145
	3	2.2817	0.2994	1.9696	-0.0455	0.0146	0.0371	2.1812	-0.0108	1.8133	-0.0383	0.0116	0.0225
	4	0.8888	-0.2286	1.8091	-0.0201	0.0182	0.0261	1.6068	1.4845	1.0413	-0.0121	0.0102	0.0155
	5	2.8036	0.2770	0.9728	-0.0125	0.0164	0.0204	0.6465	0.6648	1.3010	-0.0098	0.0080	0.0065
	6	2.9622	-0.0055	0.6480	-0.0075	0.0132	0.0187	1.0969	-0.7506	1.0358	-0.0074	0.0058	0.0071
ReturnETF	1	-0.1222	1.9910	-0.1018	0.0031	-0.0821	0.0070	0.2801	1.1938	0.2933	0.0066	-0.1798	0.0139
	2	0.2082	1.1447	-0.0747	0.0003	-0.0460	0.0241	0.5256	1.4212	0.6512	0.0069	-0.0854	0.0161
	3	-0.0206	0.9030	0.6420	0.0009	-0.0264	0.0242	0.3090	1.2978	0.6440	0.0074	-0.0506	0.0136
	4	0.4079	1.4754	0.0179	0.0001	-0.0189	0.0391	0.1716	1.3282	1.4297	0.0001	-0.0279	0.0061
	5	0.4481	1.0392	0.3042	0.0002	-0.0092	0.0223	-0.2721	1.6218	1.0144	-0.0001	-0.0192	-0.0018
	6	0.6717	2.4037	1.5288	-0.0006	-0.0089	0.0152	0.8203	2.1979	1.1174	0.0006	-0.0098	0.0018

Table 3.10 Contemporaneous and Past Correlation between Innovations of Order Imbalance and Returns

The table presents the correlation matrix for the VAR innovations in the time series of Order Imbalance and Return of ADR, ETF, and CEF. I define the price-setting buys and sells by using the algorithm developed by Lee and Ready (1991). For each 5 minute interval for all the three securities across the countries, I compute "price-setting" order imbalances by security type by subtracting the price-setting sell volume from the price-setting buy volume, and then normalizing by the stock's average 5-minute price-setting volume over the sample period. Vector Y_t can be expressed in terms of current and lagged innovations: $Y_t=A_t+\sum A_j Y_{t-j}+u_t$, where $Y_t=\{OIB_t^1, OIB_t^2, OIB_t^3, R_t^1, R_t^2, R_t^3\}$ represents net order imbalances and returns of the leading ADR, ETF, and CEF respectively. The lag length is chosen as k=6 by Akaike and Schwartz-Bayes criteria. Panel A-G show the Contemporaneous and Past Correlation of the Order Imbalance and Returns of ADR, ETF, and CEF.

Panel A: Contemporaneous Correlation of the Order Imbalance and Returns

Variable	Lag	oibnavADR	oibnavETF	oibnavCEF	return1ADR	return1ETF	return1CEF
oibnavADR	0	1.000000					
oibnavETF	0	0.005457	1.000000				
oibnavCEF	0	0.006706	0.007559	1.000000			
return1ADR	0	0.151451	0.003719	0.003323	1.00000		
return1ETF	0	0.004138	0.158846	0.003743	0.022202	1.000000	
return1CEF	0	0.005264	0.006362	0.188220	0.017294	0.017626	1.000000

Panel B: Correlation of the Current and Past Order Imbalance and Returns

Variable	Lag	oibnavADR	oibnavETF	oibnavCEF	return1ADR	return1ETF	return1CEF
oibnavADR	1	-0.001550	-0.000239	-0.000296	-0.000049	-0.000095	-0.000018
oibnavETF	1	-0.000261	-0.001831	-0.000557	-0.000007	-0.000025	-0.000135
oibnavCEF	1	-0.000259	-0.000520	-0.001197	-0.000080	-0.000133	0.000042
return1ADR	1	-0.000055	-0.000072	-0.000059	-0.000043	0.000046	0.000034
return1ETF	1	-0.000068	0.000027	-0.000079	0.000042	-0.000210	0.000038
return1CEF	1	-0.000158	-0.000128	0.000097	0.000020	0.000039	-0.000234

Panel C: Correlation of the Current and Past Order Imbalance and Returns

Variable	Lag	oibnavADR	oibnavETF	oibnavCEF	return1ADR	return1ETF	return1CEF
oibnavADR	2	-0.003093	-0.000495	-0.000528	-0.000094	-0.000213	-0.000126
oibnavETF	2	-0.000435	-0.003618	-0.001008	-0.000046	-0.000051	-0.000241
oibnavCEF	2	-0.000519	-0.000986	-0.002451	-0.000145	-0.000308	0.000076
return1ADR	2	-0.000079	-0.000125	-0.000097	-0.000084	0.000096	0.000089
return1ETF	2	-0.000216	0.000053	-0.000190	0.000074	-0.000495	0.000138
return1CEF	2	-0.000202	-0.000066	0.000372	0.000146	0.000064	-0.000334

Table 3.10 (Continued)

Panel D: Correlation of the Current and Past Order Imbalance and Returns

Variable	Lag	oibnavADR	oibnavETF	oibnavCEF	return1ADR	return1ETF	return1CEF
oibnavADR	3	-0.004853	-0.000715	-0.000887	-0.000145	-0.000339	-0.000284
oibnavETF	3	-0.000685	-0.005540	-0.001571	-0.000083	-0.000073	-0.000390
oibnavCEF	3	-0.000845	-0.001509	-0.003803	-0.000203	-0.000455	0.000127
return1ADR	3	0.000182	-0.000135	-0.000276	0.000073	0.000101	0.000656
return1ETF	3	-0.000261	0.000179	-0.000242	0.000149	-0.000774	0.000207
return1CEF	3	-0.000274	-0.000206	0.000321	0.000075	0.000153	-0.000581

Panel E: Correlation of the Current and Past Order Imbalance and Returns

Variable	Lag	oibnavADR	oibnavETF	oibnavCEF	return1ADR	return1ETF	return1CEF
oibnavADR	4	-0.006843	-0.000955	-0.001200	-0.000236	-0.000499	-0.000696
oibnavETF	4	-0.000948	-0.007891	-0.002033	-0.000127	-0.000090	-0.000578
oibnavCEF	4	-0.001148	-0.002183	-0.005423	-0.000310	-0.000613	0.000151
return1ADR	4	0.000237	-0.000180	-0.000098	-0.000064	0.000139	0.000553
return1ETF	4	-0.000349	0.000707	0.000308	0.000783	-0.002145	0.000885
return1CEF	4	-0.000398	-0.000432	0.000613	0.000126	0.000345	-0.000976

Panel F: Correlation of the Current and Past Order Imbalance and Returns

Variable	Lag	oibnavADR	oibnavETF	oibnavCEF	return1ADR	return1ETF	return1CEF
oibnavADR	5	-0.009322	-0.001289	-0.001532	-0.000365	-0.000679	-0.000816
oibnavETF	5	-0.001243	-0.010891	-0.002757	-0.000177	-0.000179	-0.000773
oibnavCEF	5	-0.001555	-0.002915	-0.007595	-0.000360	-0.000847	0.000210
return1ADR	5	0.000824	0.000190	0.000397	-0.000242	0.000840	0.000575
return1ETF	5	-0.000332	0.000764	-0.000497	0.000658	-0.001741	0.000799
return1CEF	5	-0.000306	-0.000307	0.001389	0.000245	0.000979	-0.001767

Panel F: Correlation of the Current and Past Order Imbalance and Returns

Variable	Lag	oibnavADR	oibnavETF	oibnavCEF	return1ADR	return1ETF	return1CEF
oibnavADR	6	-0.014872	-0.001871	-0.002291	-0.000561	-0.001060	-0.001168
oibnavETF	6	-0.001764	-0.016656	-0.003905	-0.000277	-0.000165	-0.001289
oibnavCEF	6	-0.002310	-0.004238	-0.012032	-0.000608	-0.001425	0.000372
return1ADR	6	0.002045	-0.000205	0.000143	-0.000732	0.001390	0.001619
return1ETF	6	-0.000384	0.001483	-0.000226	0.000341	-0.001061	0.000444
return1CEF	6	-0.000742	-0.000509	0.001555	0.000125	0.001077	-0.002528

Table 3.11 Returns Around the Largest versus Smallest Trades by the Triplets (Leading ADR, ETF, and CEF)

This table presents analysis of midquote returns around the largest v.s. smallest buying and selling activity of the three securities leading ADR, ETF, and CEF. For each security, I select the trades with the highest 5% and lowest 5% trading volume. All the trades are time-stamped in 5-minute interval. Then I calculate the average cumulative midquote returns of the three securities over windows [-k,-1], 0, [1, k], k=1, 5, 10, 15, 20, which presents the cumulative returns just before and after the largest v.s. smallest trades of one security. I also show the average cumulative midquote returns over windows [-k, 0], and [0, k], k=5, 10, 20. Panel A presents the cumulative midquote returns of leading ADR, ETF, and CEF around the largest v.s smallest trades of one security. Panel B presents the cumulative midquote returns of leading ADR, ETF, and CEF around the largest v.s smallest buying activities of one security. Panel C presents the cumulative midquote returns of leading ADR, ETF, and CEF around the largest v.s smallest selling activities of one security.

Panel A: The Cumulative Midquote Returns Around the Largest v.s. Smallest Trades

(a) Returns of ADR, ETF, and CEF Around the trades of ADR

Variable		[-20,-1]	[-15,-1]	[-10,-1]	[-5,-1]	[-1,0]	0	[0,1]	[1,5]	[1,10]	[1.15]	[1,20]	[-20,20]
ReturnADR	High5%	-0.0343	-0.0286	-0.0118	-0.0010	0.0047	0.0049	0.0072	-0.0007	-0.0053	-0.0169	-0.0210	-0.0509
ReturnETF	High5%	-0.0661	-0.0560	-0.0398	-0.0240	0.0164	0.0096	0.0148	0.0046	-0.0075	-0.0183	-0.0324	-0.0683
ReturnCEF	High5%	0.0085	0.0069	0.0065	0.0002	-0.0001	0.0004	0.0000	-0.0074	-0.0099	-0.0091	-0.0105	0.0031
ReturnADR	Low5%	-0.0323	-0.0248	-0.0158	-0.0070	-0.0048	-0.0031	-0.0061	0.0252	0.0268	0.0289	0.0298	-0.0673
ReturnETF	Low5%	0.0047	0.0036	0.0026	0.0014	0.0006	0.0004	0.0006	-0.0013	-0.0006	0.0002	0.0010	0.0169
ReturnCEF	Low5%	-0.0191	-0.0155	-0.0093	-0.0060	-0.0044	-0.0032	-0.0057	-0.0275	-0.0405	-0.0543	-0.0631	-0.0268

(b) Returns of ADR, ETF, and CEF Around the trades of ETF

Variable		[-20,-1]	[-15,-1]	[-10,-1]	[-5,-1]	[-1,0]	0	[0,1]	[1,5]	[1,10]	[1.15]	[1,20]	[-20,20]
ReturnETF	High5%	0.0347	0.0276	0.0180	0.0065	0.0054	0.0004	0.0006	0.0072	0.0162	0.0298	0.0431	0.0779
ReturnADR	High5%	-0.0245	-0.0244	-0.0160	-0.0099	-0.0063	-0.0015	-0.0011	-0.0005	-0.0036	0.0014	-0.0007	-0.0265
ReturnCEF	High5%	0.0261	0.0209	0.0139	0.0148	0.0059	0.0062	-0.0006	-0.0069	0.0001	0.0152	0.0146	0.0555
ReturnETF	Low5%	0.0039	0.0035	0.0025	0.0009	0.0011	0.0003	0.0008	0.0110	0.0152	0.0188	0.0219	0.0167
ReturnADR	Low5%	-0.0269	-0.0195	-0.0123	-0.0052	-0.0026	-0.0015	-0.0023	-0.0005	-0.0069	-0.0124	-0.0182	-0.0567
ReturnCEF	Low5%	-0.0031	-0.0029	-0.0037	-0.0047	-0.0021	-0.0014	-0.0018	-0.0401	-0.0496	-0.0603	-0.0668	-0.0006

(c) Returns of ADR, ETF, and CEF Around the trades of CEF

Variable		[-20,-1]	[-15,-1]	[-10,-1]	[-5,-1]	[-1,0]	0	[0,1]	[1,5]	[1,10]	[1.15]	[1,20]	[-20,20]
ReturnCEF	High5%	0.0251	0.0216	0.0102	-0.0042	0.0091	-0.0001	0.0022	0.0067	0.0117	0.0127	0.0260	0.0541
ReturnADR	High5%	0.0004	0.0061	0.0058	0.0037	-0.0054	-0.0008	0.0068	0.0053	-0.0049	-0.0136	-0.0069	-0.0074
ReturnETF	High5%	0.0236	0.0115	0.0049	0.0039	0.0013	0.0042	0.0001	0.0003	0.0029	0.0217	0.0213	0.0484
ReturnCEF	Low5%	0.0000	-0.0008	-0.0009	-0.0004	-0.0002	0.0001	-0.0001	-0.0137	-0.0162	-0.0184	-0.0217	0.0039
ReturnADR	Low5%	-0.0219	-0.0163	-0.0100	-0.0054	-0.0021	-0.0010	-0.0015	0.0049	0.0023	-0.0006	-0.0036	-0.0429
ReturnETF	Low5%	0.0087	0.0068	0.0048	0.0023	0.0007	0.0003	0.0005	-0.0002	0.0014	0.0029	0.0051	0.0187

Table 3.11 (Continued)

(d) Compare returns among ADR, ETF, and CEF aroung the largest and smallest trades

Return		K=-20	-10	-5	0	5	10	20
ADR	High 5%	-0.0297	-0.0071	0.0037	0.0049	0.0042	-0.0004	-0.0161
	Low 5%	-0.0354	-0.0189	-0.0101	-0.0031	-0.0137	-0.0202	-0.0334
	Difference	0.0057	0.0118	0.0138	0.0080	0.0179	0.0198	0.0174
ETF	High 5%	0.0348	0.0181	0.0066	0.0004	0.0074	0.0164	0.0433
	Low 5%	0.0043	0.0029	0.0013	0.0003	0.0029	0.0050	0.0076
	Difference	0.0304	0.0153	0.0053	0.0000	0.0045	0.0113	0.0357
CEF	High 5%	0.0274	0.0126	-0.0026	-0.0001	0.0065	0.0116	0.0259
	Low 5%	0.0000	-0.0009	-0.0003	0.0001	-0.0004	0.0005	0.0023
	Difference	0.0274	0.0135	-0.0022	-0.0002	0.0069	0.0111	0.0236
ADR-ETF	High 5%	-0.0644	-0.0252	-0.0030	0.0045	-0.0032	-0.0168	-0.0594
	Low 5%	-0.0397	-0.0217	-0.0114	-0.0034	-0.0165	-0.0252	-0.0411
ETF-CEF	High 5%	0.0073	0.0055	0.0092	0.0005	0.0009	0.0048	0.0174
	Low 5%	0.0043	0.0037	0.0017	0.0002	0.0033	0.0045	0.0053
ADR-CEF	High 5%	-0.0571	-0.0197	0.0062	0.0050	-0.0023	-0.0120	-0.0419
	Low 5%	-0.0354	-0.0180	-0.0098	-0.0032	-0.0133	-0.0207	-0.0357

Panel B: The Cumulative Midquote Returns Around the Largest v.s. Smallest Buys

(a) Returns of ADR, ETF, and CEF Around the Buys of ADR

Variable		[-20,-1]	[-15,-1]	[-10,-1]	[-5,-1]	[-1,0]	0	[0,1]	[1,5]	[1,10]	[1.15]	[1,20]	[-20,20]
ReturnADR	High5%	-0.0787	-0.0598	-0.0401	-0.0201	-0.0127	-0.0082	-0.0096	-0.0165	-0.0364	-0.0555	-0.0748	-0.1617
ReturnETF	High5%	-0.0193	-0.0142	-0.0094	-0.0045	-0.0015	-0.0007	-0.0017	-0.0047	-0.0094	-0.0138	-0.0184	-0.0384
ReturnCEF	High5%	-0.0509	-0.0385	-0.0255	-0.0128	-0.0043	-0.0019	-0.0042	-0.0132	-0.0263	-0.0396	-0.0520	-0.1048
ReturnADR	Low5%	-0.0656	-0.0491	-0.0327	-0.0161	-0.0037	-0.0006	-0.0052	-0.0170	-0.0329	-0.0488	-0.0649	-0.1324
ReturnETF	Low5%	-0.0230	-0.0172	-0.0115	-0.0057	-0.0024	-0.0013	-0.0025	-0.0057	-0.0115	-0.0173	-0.0233	-0.0478
ReturnCEF	Low5%	-0.0501	-0.0374	-0.0249	-0.0124	-0.0056	-0.0031	-0.0056	-0.0129	-0.0252	-0.0376	-0.0502	-0.1026

(b) Returns of ADR, ETF, and CEF Around the Buys of ETF

Variable		[-20,-1]	[-15,-1]	[-10,-1]	[-5,-1]	[-1,0]	0	[0,1]	[1,5]	[1,10]	[1.15]	[1,20]	[-20,20]
ReturnETF	High5%	-0.0464	-0.0353	-0.0239	-0.0125	-0.0112	-0.0084	-0.0089	-0.0084	-0.0194	-0.0306	-0.0413	-0.0962
ReturnADR	High5%	-0.0468	-0.0349	-0.0233	-0.0115	-0.0043	-0.0020	-0.0043	-0.0117	-0.0235	-0.0355	-0.0466	-0.0955
ReturnCEF	High5%	-0.0515	-0.0387	-0.0262	-0.0136	-0.0049	-0.0018	-0.0048	-0.0136	-0.0256	-0.0381	-0.0514	-0.1047
ReturnETF	Low5%	-0.0316	-0.0236	-0.0157	-0.0077	-0.0017	-0.0002	-0.0023	-0.0085	-0.0162	-0.0239	-0.0316	-0.0637
ReturnADR	Low5%	-0.0599	-0.0449	-0.0300	-0.0150	-0.0061	-0.0031	-0.0061	-0.0146	-0.0295	-0.0444	-0.0592	-0.1228
ReturnCEF	Low5%	-0.0559	-0.0419	-0.0280	-0.0141	-0.0060	-0.0031	-0.0059	-0.0152	-0.0291	-0.0432	-0.0571	-0.1141

Table 3.11 (Continued)

(c) Returns of ADR, ETF, and CEF Around the Buys of CEF

Variable		[-20,-1]	[-15,-1]	[-10,-1]	[-5,-1]	[-1,0]	0	[0,1]	[1,5]	[1,10]	[1.15]	[1,20]	[-20,20]
ReturnCEF	High5%	-0.0736	-0.0580	-0.0405	-0.0235	-0.0313	-0.0253	-0.0255	-0.0114	-0.0292	-0.0468	-0.0633	-0.1619
ReturnADR	High5%	-0.0602	-0.0446	-0.0301	-0.0145	-0.0049	-0.0022	-0.0048	-0.0158	-0.0326	-0.0481	-0.0635	-0.1259
ReturnETF	High5%	-0.0256	-0.0185	-0.0122	-0.0057	-0.0016	-0.0006	-0.0024	-0.0076	-0.0143	-0.0202	-0.0266	-0.0528
ReturnCEF	Low5%	-0.0502	-0.0375	-0.0249	-0.0123	-0.0027	-0.0004	-0.0033	-0.0136	-0.0263	-0.0389	-0.0517	-0.1016
ReturnADR	Low5%	-0.0651	-0.0488	-0.0326	-0.0163	-0.0066	-0.0033	-0.0065	-0.0160	-0.0322	-0.0484	-0.0647	-0.1334
ReturnETF	Low5%	-0.0323	-0.0243	-0.0162	-0.0081	-0.0033	-0.0017	-0.0033	-0.0079	-0.0160	-0.0240	-0.0321	-0.0663

(d) Compare returns among ADR, ETF, and CEF aroung the largest and smallest trades

ReturnBuy		K=-20	-10	-5	0	5	10	20
ADR	High 5%	-0.0869	-0.0483	-0.0283	-0.0082	-0.0247	-0.0446	-0.0830
	Low 5%	-0.0662	-0.0333	-0.0167	-0.0006	-0.0184	-0.0345	-0.0668
	Difference	-0.0207	-0.0150	-0.0116	-0.0076	-0.0063	-0.0101	-0.0162
ETF	High 5%	-0.0548	-0.0323	-0.0209	-0.0084	-0.0169	-0.0278	-0.0498
	Low 5%	-0.0318	-0.0159	-0.0079	-0.0002	-0.0089	-0.0166	-0.0321
	Difference	-0.0231	-0.0164	-0.0130	-0.0083	-0.0080	-0.0112	-0.0177
CEF	High 5%	-0.0986	-0.0656	-0.0485	-0.0253	-0.0367	-0.0545	-0.0886
	Low 5%	-0.0506	-0.0252	-0.0127	-0.0004	-0.0136	-0.0262	-0.0515
	Difference	-0.0481	-0.0403	-0.0358	-0.0249	-0.0231	-0.0282	-0.0371
ADR-ETF	High 5%	-0.0321	-0.0160	-0.0074	0.0002	-0.0078	-0.0167	-0.0333
	Low 5%	-0.0344	-0.0174	-0.0088	-0.0004	-0.0095	-0.0178	-0.0347
ETF-CEF	High 5%	0.0438	0.0333	0.0276	0.0169	0.0199	0.0266	0.0388
	Low 5%	0.0188	0.0094	0.0047	0.0002	0.0048	0.0096	0.0194
ADR-CEF	High 5%	0.0117	0.0172	0.0202	0.0171	0.0121	0.0099	0.0056
	Low 5%	-0.0156	-0.0080	-0.0040	-0.0002	-0.0047	-0.0082	-0.0153

Panel C: The Cumulative Midquote Returns Around the Largest v.s. Smallest Sells

(a) Returns of ADR, ETF, and CEF Around the Sells of ADR

Variable		[-20,-1]	[-15,-1]	[-10,-1]	[-5,-1]	[-1,0]	0	[0,1]	[1,5]	[1,10]	[1.15]	[1,20]	[-20,20]
ReturnADR	High 5%	0.0829	0.0628	0.0428	0.0224	0.0143	0.0096	0.0116	0.0196	0.0409	0.0620	0.0827	0.1753
ReturnETF	High 5%	0.0171	0.0131	0.0098	0.0050	0.0046	0.0025	0.0053	0.0065	0.0083	0.0121	0.0160	0.0358
ReturnCEF	High 5%	0.0523	0.0387	0.0262	0.0133	0.0041	0.0018	0.0042	0.0127	0.0261	0.0393	0.0521	0.1064
ReturnADR	Low 5%	0.0586	0.0437	0.0289	0.0143	0.0031	0.0004	0.0044	0.0161	0.0305	0.0451	0.0598	0.1179
ReturnETF	Low 5%	0.0235	0.0176	0.0117	0.0060	0.0025	0.0013	0.0025	0.0063	0.0122	0.0182	0.0241	0.0489
ReturnCEF	Low 5%	0.0492	0.0368	0.0245	0.0122	0.0054	0.0029	0.0054	0.0116	0.0234	0.0355	0.0476	0.1011

Table 3.11 (Continued)

(b) Returns of ADR, ETF, and CEF Around the Sells of ETF

Variable		[-20,-1]	[-15,-1]	[-10,-1]	[-5,-1]	[-1,0]	0	[0,1]	[1,5]	[1,10]	[1.15]	[1,20]	[-20,20]
ReturnETF	High 5%	0.0477	0.0364	0.0251	0.0128	0.0127	0.0097	0.0105	0.0097	0.0220	0.0339	0.0460	0.1035
ReturnADR	High 5%	0.0471	0.0341	0.0231	0.0115	0.0038	0.0017	0.0042	0.0119	0.0242	0.0370	0.0484	0.0972
ReturnCEF	High 5%	0.0553	0.0417	0.0275	0.0145	0.0051	0.0025	0.0052	0.0131	0.0273	0.0412	0.0548	0.1127
ReturnETF	Low 5%	0.0322	0.0241	0.0160	0.0079	0.0016	0.0001	0.0021	0.0089	0.0171	0.0252	0.0334	0.0654
ReturnADR	Low 5%	0.0565	0.0424	0.0283	0.0142	0.0058	0.0029	0.0058	0.0143	0.0285	0.0426	0.0567	0.1159
ReturnCEF	Low 5%	0.0544	0.0407	0.0271	0.0134	0.0054	0.0028	0.0054	0.0114	0.0245	0.0376	0.0507	0.1116

(c) Returns of ADR, ETF, and CEF Around the Sells of CEF

Variable		[-20,-1]	[-15,-1]	[-10,-1]	[-5,-1]	[-1,0]	0	[0,1]	[1,5]	[1,10]	[1.15]	[1,20]	[-20,20]
ReturnCEF	High 5%	0.0805	0.0624	0.0432	0.0205	0.0326	0.0256	0.0257	0.0127	0.0314	0.0512	0.0712	0.1772
ReturnADR	High 5%	0.0610	0.0452	0.0301	0.0151	0.0046	0.0024	0.0054	0.0150	0.0291	0.0444	0.0605	0.1238
ReturnETF	High 5%	0.0280	0.0206	0.0140	0.0074	0.0028	0.0012	0.0029	0.0074	0.0145	0.0224	0.0291	0.0581
ReturnCEF	Low 5%	0.0504	0.0376	0.0250	0.0123	0.0027	0.0003	0.0032	0.0124	0.0248	0.0372	0.0497	0.1021
ReturnADR	Low 5%	0.0631	0.0473	0.0316	0.0158	0.0064	0.0032	0.0064	0.0159	0.0317	0.0475	0.0633	0.1294
ReturnETF	Low 5%	0.0337	0.0253	0.0169	0.0084	0.0034	0.0017	0.0034	0.0084	0.0168	0.0252	0.0336	0.0691

(d) Compare returns among ADR, ETF, and CEF aroung the largest and smallest trades

ReturnBuy		K=-20	-10	-5	0	5	10	20
ADR	High 5%	0.0925	0.0524	0.0319	0.0096	0.0292	0.0504	0.0923
	Low 5%	0.0589	0.0293	0.0147	0.0004	0.0160	0.0303	0.0593
	Difference	0.0336	0.0231	0.0172	0.0092	0.0132	0.0202	0.0330
ETF	High 5%	0.0574	0.0348	0.0225	0.0097	0.0194	0.0317	0.0557
	Low 5%	0.0323	0.0160	0.0079	0.0001	0.0086	0.0166	0.0328
	Difference	0.0251	0.0187	0.0146	0.0096	0.0108	0.0150	0.0230
CEF	High 5%	0.1062	0.0690	0.0461	0.0256	0.0383	0.0570	0.0968
	Low 5%	0.0507	0.0253	0.0126	0.0003	0.0136	0.0263	0.0516
	Difference	0.0555	0.0437	0.0335	0.0253	0.0247	0.0308	0.0452
ADR-ETF	High 5%	0.0351	0.0176	0.0094	-0.0001	0.0097	0.0188	0.0366
	Low 5%	0.0266	0.0133	0.0068	0.0003	0.0074	0.0136	0.0265
ETF-CEF	High 5%	-0.0488	-0.0342	-0.0235	-0.0159	-0.0188	-0.0253	-0.0411
	Low 5%	-0.0184	-0.0092	-0.0046	-0.0002	-0.0050	-0.0096	-0.0188
ADR-CEF	High 5%	-0.0137	-0.0166	-0.0141	-0.0160	-0.0091	-0.0066	-0.0045
	Low 5%	0.0082	0.0040	0.0021	0.0001	0.0024	0.0040	0.0077

Table 3.12 Prices Around the Largest versus Smallest Trades by the Triplets (Leading ADR, ETF, and CEF)

This table presents analysis of prices around the largest v.s. smallest buying and selling activity of the three securities leading ADR, ETF, and CEF. For each security, I select the trades with the highest 5% and lowest 5% trading volume. All the trades are time-stamped in 5-minute interval. Then I calculate the average prices of the three securities over windows [-k,-1], 0, [1, k], k=1, 5, 10, 15, 20, which presents the average prices just before and after the largest v.s. smallest trades of one security. I also show the average prices over windows [-k, 0], and [0, k], k=5, 10, 20. Panel A presents the average prices of leading ADR, ETF, and CEF around the largest v.s smallest trades of one security. Panel B presents the average prices of leading ADR, ETF, and CEF around the largest v.s smallest buying activities of one security. Panel C presents the average prices of leading ADR, ETF, and CEF around the largest v.s smallest selling activities of one security.

Panel A: Average Price Around the Largest v.s. Smallest Trades

(a) Average Price of ADR, ETF, and CEF Around the trades of ADR

Variable		[-20,-1]	[-15,-1]	[-10,-1]	[-5,-1]	[-1,0]	0	[0,1]	[1,5]	[1,10]	[1.15]	[1,20]	[-20,20]
PriceADR	High5%	33.600	31.891	31.950	32.047	33.655	34.974	33.595	31.977	31.901	31.877	31.850	31.925
PriceETF	High5%	5.478	5.244	5.243	5.230	4.996	4.801	4.964	5.219	5.232	5.232	5.227	5.223
PriceCEF	High5%	5.025	4.838	4.842	4.815	4.367	4.000	4.359	4.816	4.823	4.819	4.813	4.800
PriceADR	Low5%	36.611	35.156	35.066	34.904	31.116	27.791	31.126	34.900	35.055	35.143	35.206	35.043
PriceETF	Low5%	8.638	8.190	8.188	8.193	8.427	8.673	8.442	8.175	8.191	8.197	8.208	8.223
PriceCEF	Low5%	6.110	5.743	5.741	5.775	6.496	7.128	6.482	5.739	5.748	5.769	5.796	5.808

(b) Average Price of ADR, ETF, and CEF Around the trades of ETF

Variable		[-20,-1]	[-15,-1]	[-10,-1]	[-5,-1]	[-1,0]	0	[0,1]	[1,5]	[1,10]	[1.15]	[1,20]	[-20,20]
PriceETF	High5%	25.380	23.723	23.894	24.132	30.046	34.994	29.633	23.786	23.641	23.534	23.465	23.824
PriceADR	High5%	35.371	33.840	33.735	33.658	32.029	30.468	31.949	33.678	33.784	33.859	33.888	33.790
PriceCEF	High5%	7.078	6.784	6.798	6.803	6.416	6.143	6.410	6.722	6.733	6.715	6.682	6.711
PriceETF	Low5%	18.406	17.760	17.677	17.543	14.451	11.705	14.486	17.582	17.691	17.769	17.817	17.683
PriceADR	Low5%	36.795	35.005	35.017	35.039	35.513	35.923	35.510	35.037	35.013	35.001	34.995	35.022
PriceCEF	Low5%	6.095	5.777	5.778	5.791	6.064	6.298	6.069	5.801	5.798	5.801	5.806	5.805

(c) Average Price of ADR, ETF, and CEF Around the trades of CEF

Variable		[-20,-1]	[-15,-1]	[-10,-1]	[-5,-1]	[-1,0]	0	[0,1]	[1,5]	[1,10]	[1.15]	[1,20]	[-20,20]
PriceCEF	High5%	7.407	6.759	6.853	7.047	11.091	14.563	11.033	6.979	6.793	6.705	6.646	6.855
PriceADR	High5%	36.659	35.175	35.105	34.898	31.326	28.407	31.259	34.830	35.070	35.165	35.220	35.065
PriceETF	High5%	21.253	20.378	20.335	20.227	18.547	17.185	18.594	20.229	20.292	20.336	20.348	20.304
PriceCEF	Low5%	5.492	5.357	5.310	5.229	3.509	2.004	3.512	5.237	5.317	5.363	5.398	5.312
PriceADR	Low5%	36.583	34.783	34.799	34.832	35.557	36.176	35.564	34.834	34.798	34.782	34.772	34.809
PriceETF	Low5%	27.595	26.213	26.233	26.272	27.094	27.806	27.083	26.246	26.203	26.184	26.177	26.234

Table 3.12 (Continued)

(d) Compare prices among ADR, ETF, and CEF aroung the largest and smallest trades

Price		K=-20	-10	-5	0	5	10	20
ADR	High 5%	31.9996	32.2245	32.5349	34.9736	32.4761	32.1803	31.9984
	Low 5%	34.8676	34.4048	33.7187	27.7912	33.7339	34.4120	34.8688
	Difference	-2.8680	-2.1803	-1.1838	7.1824	-1.2578	-2.2317	-2.8704
ETF	High 5%	24.1712	24.9034	25.9425	34.9941	25.6537	24.6724	24.0138
	Low 5%	17.5300	17.1343	16.5700	11.7052	16.6128	17.1593	17.5392
	Difference	6.6413	7.7690	9.3725	23.2889	9.0409	7.5131	6.4746
CEF	High 5%	7.0545	7.5536	8.2999	14.5630	8.2427	7.4994	7.0229
	Low 5%	5.2309	5.0094	4.6917	2.0042	4.6976	5.0151	5.2362
	Difference	1.8236	2.5442	3.6082	12.5589	3.5451	2.4844	1.7867
ADR-ETF	High 5%	7.8283	7.3212	6.5924	-0.0206	6.8224	7.5079	7.9846
	Low 5%	17.3376	17.2705	17.1487	16.0860	17.1211	17.2527	17.3296
ETF-CEF	High 5%	17.1167	17.3498	17.6426	20.4311	17.4109	17.1730	16.9909
	Low 5%	12.2990	12.1249	11.8783	9.7010	11.9152	12.1442	12.3030
ADR-CEF	High 5%	24.9450	24.6710	24.2350	20.4105	24.2334	24.6809	24.9756
	Low 5%	29.6367	29.3954	29.0270	25.7870	29.0363	29.3969	29.6326

Panel B: Average Price Around the Largest v.s. Smallest Buys

(a) Average Price of ADR, ETF, and CEF Around the Buys of ADR

Variable		[-20,-1]	[-15,-1]	[-10,-1]	[-5,-1]	[-1,0]	0	[0,1]	[1,5]	[1,10]	[1.15]	[1,20]	[-20,20]
PriceADR	High5%	18.453	17.080	17.223	17.571	23.881	29.104	23.649	17.405	17.180	17.058	16.973	17.281
PriceETF	High5%	3.340	3.192	3.189	3.181	3.064	2.972	3.040	3.180	3.180	3.184	3.184	3.183
PriceCEF	High5%	2.443	2.347	2.355	2.346	2.229	2.107	2.221	2.341	2.354	2.344	2.337	2.332
PriceADR	Low5%	16.178	15.989	15.824	15.483	7.966	1.628	7.962	15.463	15.804	15.974	16.087	15.742
PriceETF	Low5%	4.539	4.321	4.323	4.321	4.327	4.349	4.325	4.303	4.306	4.318	4.324	4.324
PriceCEF	Low5%	2.718	2.578	2.568	2.574	2.637	2.700	2.610	2.548	2.560	2.570	2.584	2.586

(b) Average Price of ADR, ETF, and CEF Around the Buys of ETF

Variable		[-20,-1]	[-15,-1]	[-10,-1]	[-5,-1]	[-1,0]	0	[0,1]	[1,5]	[1,10]	[1.15]	[1,20]	[-20,20]
PriceETF	High5%	16.576	15.132	15.352	15.717	24.136	31.364	23.827	15.432	15.200	15.046	14.960	15.383
PriceADR	High5%	18.314	17.526	17.482	17.494	16.677	15.805	16.473	17.332	17.443	17.422	17.426	17.434
PriceCEF	High5%	3.839	3.676	3.696	3.688	3.516	3.350	3.509	3.676	3.670	3.660	3.637	3.647
PriceETF	Low5%	10.893	10.748	10.613	10.344	5.276	1.000	5.282	10.347	10.613	10.744	10.835	10.606
PriceADR	Low5%	18.930	18.019	18.020	18.025	18.130	18 15	18.126	18.031	18.030	18.028	18.029	18.030
PriceCEF	Low5%	3.166	3.001	2.995	3.001	3.116	3.214	3.115	3.005	3.003	3.004	3.007	3.011

Table 3.12 (Continued)

(c) Average Price of ADR, ETF, and CEF Around the Buys of CEF

Variable		[-20,-1]	[-15,-1]	[-10,-1]	[-5,-1]	[-1,0]	0	[0,1]	[1,5]	[1,10]	[1.15]	[1,20]	[-20,20]
PriceCEF	High5%	4.540	3.915	4.036	4.269	9.715	14.348	9.518	4.141	3.937	3.837	3.782	4.059
PriceADR	High5%	18.278	17.497	17.415	17.399	15.839	14.536	15.860	17.385	17.464	17.492	17.530	17.469
PriceETF	High5%	14.017	13.431	13.395	13.383	12.186	11.361	12.165	13.286	13.340	13.371	13.402	13.380
PriceCEF	Low5%	2.870	2.830	2.792	2.725	1.414	0.296	1.417	2.725	2.792	2.829	2.854	2.792
PriceADR	Low5%	19.054	18.135	18.136	18.143	18.260	18.374	18.268	18.152	18.146	18.146	18.144	18.147
PriceETF	Low5%	16.043	15.258	15.260	15.265	15.542	15.784	15.549	15.269	15.251	15.252	15.249	15.267

(d) Compare prices among ADR, ETF, and CEF aroung the largest and smallest trades

Price		K=-20	-10	-5	0	5	10	20
ADR	High 5%	17.5740	18.3033	19.4936	29.1044	19.3549	18.2638	17.5504
	Low 5%	15.4079	14.5337	13.1739	1.6279	13.1612	14.5190	15.4027
	Difference	2.1661	3.7695	6.3198	27.4765	6.1936	3.7449	2.1476
ETF	High 5%	15.7871	16.8080	18.3250	31.3636	18.0868	16.6689	15.7412
	Low 5%	10.3746	9.7391	8.7867	0.9998	8.7931	9.7440	10.3727
	Difference	5.4124	7.0689	9.5383	30.3638	9.2937	6.9249	5.3684
CEF	High 5%	4.3236	4.9734	5.9486	14.3477	5.8420	4.8838	4.2851
	Low 5%	2.7335	2.5655	2.3203	0.2961	2.3203	2.5650	2.7319
	Difference	1.5901	2.4079	3.6283	14.0516	3.5217	2.3188	1.5532
ADR-ETF	High 5%	1.7870	1.4953	1.1686	-2.2593	1.2680	1.5949	1.8092
	Low 5%	5.0332	4.7946	4.3872	0.6281	4.3681	4.7749	5.0300
ETF-CEF	High 5%	11.4635	11.8346	12.3765	17.0159	12.2448	11.7851	11.4560
	Low 5%	7.6412	7.1736	6.4664	0.7037	6.4728	7.1791	7.6408
ADR-CEF	High 5%	13.2504	13.3298	13.5451	14.7566	13.5129	13.3800	13.2652
	Low 5%	12.6744	11.9682	10.8536	1.3318	10.8409	11.9540	12.6708

Panel C: Average Price Around the Largest v.s. Smallest Sells

(a) Average Price of ADR, ETF, and CEF Around the Sells of ADR

Variable		[-20,-1]	[-15,-1]	[-10,-1]	[-5,-1]	[-1,0]	0	[0,1]	[1,5]	[1,10]	[1.15]	[1,20]	[-20,20]
PriceADR	High5%	15.946	14.673	14.527	14.145	21.802	27.346	21.527	14.932	14.658	14.544	14.469	14.835
PriceETF	High5%	2.228	2.139	2.154	2.160	2.019	1.918	2.034	2.134	2.124	2.114	2.105	2.114
PriceCEF	High5%	2.277	2.193	2.196	2.181	2.014	1.852	1.986	2.175	2.189	2.190	2.186	2.177
PriceADR	Low5%	14.130	13.977	13.826	13.514	6.774	1.083	6.776	13.502	13.823	13.970	14.064	13.755
PriceETF	Low5%	2.844	2.699	2.692	2.687	2.734	2.775	2.741	2.688	2.697	2.705	2.715	2.713
PriceCEF	Low5%	2.482	2.348	2.337	2.330	2.395	2.469	2.393	2.325	2.332	2.344	2.355	2.360

Table 3.12 (Continued)

(b) Average Price of ADR, ETF, and CEF Around the Sells of ETF

Variable		[-20,-1]	[-15,-1]	[-10,-1]	[-5,-1]	[-1,0]	0	[0,1]	[1,5]	[1,10]	[1.15]	[1,20]	[-20,20]
PriceETF	High5%	12.224	10.883	10.767	10.683	21.745	30.133	21.413	11.423	10.904	10.698	10.527	11.091
PriceADR	High5%	15.650	14.990	14.951	14.907	14.341	13.707	14.308	14.968	15.019	14.973	14.923	14.920
PriceCEF	High5%	3.270	3.125	3.132	3.162	3.001	2.837	3.036	3.162	3.115	3.095	3.088	3.102
PriceETF	Low5%	6.714	6.628	6.528	6.331	3.025	0.267	3.021	6.313	6.512	6.618	6.694	6.544
PriceADR	Low5%	15.896	15.130	15.127	15.128	15.215	15.297	15.215	15.132	15.131	15.132	15.132	15.136
PriceCEF	Low5%	2.765	2.628	2.625	2.621	2.655	2.692	2.656	2.622	2.629	2.634	2.637	2.635

(c) Average Price of ADR, ETF, and CEF Around the Sells of CEF

Variable		[-20,-1]	[-15,-1]	[-10,-1]	[-5,-1]	[-1,0]	0	[0,1]	[1,5]	[1,10]	[1.15]	[1,20]	[-20,20]
PriceCEF	High5%	3.914	3.711	3.431	3.304	8.976	13.566	8.842	3.516	3.303	3.210	3.154	3.447
PriceADR	High5%	15.952	15.346	15.326	15.367	13.822	12.586	13.782	15.143	15.195	15.243	15.279	15.235
PriceETF	High5%	7.996	7.648	7.656	7.693	7.279	6.825	7.322	7.736	7.748	7.730	7.733	7.678
PriceCEF	Low5%	2.549	2.518	2.487	2.430	1.236	0.213	1.236	2.432	2.489	2.519	2.539	2.482
PriceADR	Low5%	15.738	14.977	14.977	14.981	15.107	15.217	15.109	14.985	14.979	14.979	14.981	14.986
PriceETF	Low5%	10.833	10.302	10.295	10.291	10.402	10.507	10.396	10.283	10.284	10.287	10.290	10.305

(d) Compare prices among ADR, ETF, and CEF aroung the largest and smallest trades

Price		K=-20	-10	-5	0	5	10	20
ADR	High 5%	15.1869	15.9650	17.1780	27.3465	17.0010	15.8116	15.0820
	Low 5%	13.4567	12.6677	11.4418	1.0830	11.4360	12.6689	13.4492
	Difference	1.7302	3.2973	5.7362	26.2634	5.5650	3.1427	1.6327
ETF	High 5%	11.6416	12.8916	14.7578	30.1331	14.5415	12.6523	11.4606
	Low 5%	6.3943	5.9584	5.3204	0.2666	5.3085	5.9478	6.3916
	Difference	5.2473	6.9332	9.4374	29.8666	9.2330	6.7045	5.0690
CEF	High 5%	3.7273	4.3524	5.3482	13.5665	5.1911	4.2360	3.6499
	Low 5%	2.4273	2.2806	2.0601	0.2127	2.0619	2.2820	2.4284
	Difference	1.3000	2.0718	3.2880	13.3537	3.1292	1.9539	1.2215
ADR-ETF	High 5%	3.5452	3.0734	2.4202	-2.7867	2.4595	3.1593	3.6213
	Low 5%	7.0624	6.7092	6.1214	0.8164	6.1275	6.7210	7.0576
ETF-CEF	High 5%	7.9144	8.5393	9.4096	16.5667	9.3505	8.4164	7.8108
	Low 5%	3.9671	3.6779	3.2602	0.0539	3.2466	3.6658	3.9632
ADR-CEF	High 5%	11.4596	11.6126	11.8298	13.7800	11.8099	11.5756	11.4321
	Low 5%	11.0294	10.3871	9.3816	0.8703	9.3742	10.3868	11.0209

Table 3.13 Qspread Around the Largest versus Smallest Trades by the Triplets (Leading ADR, ETF, and CEF)

This table presents analysis of quote spreads around the largest v.s. smallest buying and selling activity of the three securities leading ADR, ETF, and CEF. For each security, I select the trades with the highest 5% and lowest 5% trading volume. All the trades are time-stamped in 5-minute interval. Quote spread is computed as (ask – bid)/(ask + bid)/2. Then I calculate the average quote spreads of the three securities over windows [-k,-1], 0, [1, k], k=1, 5, 10, 15, 20, which presents the average quote spreads just before and after the largest v.s. smallest trades of one security. I also show the average quote spreads over windows [-k, 0], and [0, k], k=5, 10, 20. Panel A presents the average quote spreads of leading ADR, ETF, and CEF around the largest v.s smallest trades of one security. Panel B presents the average quote spreads of leading ADR, ETF, and CEF around the largest v.s smallest buying activities of one security. Panel C presents the average quote spreads of leading ADR, ETF, and CEF around the largest v.s smallest selling activities of one security.

Panel A: Average Qspread Around the Largest v.s. Smallest Trades

(a) Average Qspread of ADR, ETF, and CEF Around the trades of ADR

Variable		[-20,-1]	[-15,-1]	[-10,-1]	[-5,-1]	[-1,0]	0	[0,1]	[1,5]	[1,10]	[1.15]	[1,20]	[-20,20]
QspreadADR	High5%	0.2106	0.2110	0.2115	0.2120	0.2302	0.2468	0.2344	0.2137	0.2114	0.2107	0.2102	0.4126
QspreadETF	High5%	0.0522	0.0523	0.0524	0.0519	0.0480	0.0449	0.0482	0.0523	0.0520	0.0519	0.0516	0.1010
QspreadCEF	High5%	0.0897	0.0901	0.0904	0.0905	0.0807	0.0718	0.0807	0.0906	0.0904	0.0903	0.0901	0.1747
QspreadADR	Low5%	0.2222	0.2217	0.2212	0.2208	0.1946	0.1689	0.1923	0.2185	0.2193	0.2200	0.2206	0.4297
QspreadETF	Low5%	0.0563	0.0561	0.0559	0.0563	0.0640	0.0705	0.0645	0.0558	0.0556	0.0557	0.0560	0.1104
QspreadCEF	Low5%	0.0964	0.0961	0.0961	0.0967	0.1163	0.1330	0.1160	0.0959	0.0954	0.0956	0.0960	0.1896

(b) Average Qspread of ADR, ETF, and CEF Around the trades of ETF

Variable		[-20,-1]	[-15,-1]	[-10,-1]	[-5,-1]	[-1,0]	0	[0,1]	[1,5]	[1,10]	[1.15]	[1,20]	[-20,20]
QspreadETF	High5%	0.1355	0.1371	0.1396	0.1429	0.2402	0.3253	0.2385	0.1412	0.1374	0.1353	0.1339	0.2721
QspreadADR	High5%	0.1593	0.1587	0.1589	0.1581	0.1470	0.1355	0.1463	0.1596	0.1597	0.1597	0.1599	0.3105
QspreadCEF	High5%	0.1291	0.1293	0.1295	0.1299	0.1178	0.1090	0.1175	0.1275	0.1271	0.1267	0.1264	0.2485
QspreadETF	Low5%	0.1056	0.1051	0.1044	0.1035	0.0779	0.0545	0.0783	0.1035	0.1046	0.1053	0.1057	0.2040
QspreadADR	Low5%	0.1925	0.1925	0.1926	0.1927	0.1968	0.2005	0.1968	0.1926	0.1924	0.1925	0.1925	0.3762
QspreadCEF	Low5%	0.1193	0.1192	0.1192	0.1195	0.1293	0.1380	0.1297	0.1198	0.1196	0.1196	0.1197	0.2338

(c) Average Qspread of ADR, ETF, and CEF Around the trades of CEF

Variable		[-20,-1]	[-15,-1]	[-10,-1]	[-5,-1]	[-1,0]	0	[0,1]	[1,5]	[1,10]	[1.15]	[1,20]	[-20,20]
QspreadCEF	High5%	0.1337	0.1358	0.1380	0.1434	0.2517	0.3455	0.2534	0.1439	0.1381	0.1351	0.1334	0.2707
QspreadADR	High5%	0.2318	0.2318	0.2320	0.2318	0.2008	0.1751	0.2008	0.2324	0.2332	0.2332	0.2328	0.4508
QspreadETF	High5%	0.1058	0.1061	0.1064	0.1069	0.0939	0.0820	0.0940	0.1071	0.1066	0.1064	0.1058	0.2055
QspreadCEF	Low5%	0.1009	0.1003	0.0995	0.0981	0.0623	0.0303	0.0622	0.0978	0.0992	0.1001	0.1007	0.1934
QspreadADR	Low5%	0.2117	0.2117	0.2116	0.2118	0.2186	0.2247	0.2186	0.2115	0.2114	0.2114	0.2115	0.4137
QspreadETF	Low5%	0.1189	0.1189	0.1188	0.1189	0.1242	0.1289	0.1238	0.1185	0.1185	0.1186	0.1188	0.2326

Table 3.13 (Continued)

(d) Compare Qspreads among ADR, ETF, and CEF aroung the largest and smallest trades

Price		K=-20	-10	-5	0	5	10	20
ADR	High 5%	0.2124	0.2147	0.2178	0.2468	0.2192	0.2146	0.2120
	Low 5%	0.2197	0.2164	0.2121	0.1689	0.2102	0.2147	0.2181
	Difference	-0.0073	-0.0017	0.0057	0.0779	0.0090	0.0000	-0.0061
ETF	High 5%	0.1445	0.1565	0.1733	0.3253	0.1719	0.1544	0.1430
	Low 5%	0.1031	0.0999	0.0953	0.0545	0.0954	0.1001	0.1033
	Difference	0.0414	0.0566	0.0779	0.2708	0.0766	0.0544	0.0397
CEF	High 5%	0.1438	0.1569	0.1771	0.3455	0.1775	0.1570	0.1435
	Low 5%	0.0975	0.0932	0.0868	0.0303	0.0865	0.0929	0.0973
	Difference	0.0462	0.0637	0.0902	0.3153	0.0910	0.0641	0.0462
ADR-ETF	High 5%	0.0678	0.0582	0.0446	-0.0784	0.0473	0.0602	0.0690
	Low 5%	0.1166	0.1166	0.1168	0.1144	0.1148	0.1146	0.1147
ETF-CEF	High 5%	0.0008	-0.0004	-0.0038	-0.0203	-0.0056	-0.0025	-0.0005
	Low 5%	0.0056	0.0067	0.0085	0.0242	0.0089	0.0072	0.0060
ADR-CEF	High 5%	0.0686	0.0578	0.0408	-0.0987	0.0417	0.0577	0.0685
	Low 5%	0.1222	0.1232	0.1253	0.1386	0.1237	0.1218	0.1208

Panel B: Average Qspread Around the Largest v.s. Smallest Buys

(a) Average Qspread of ADR, ETF, and CEF Around the Buys of ADR

Variable		[-20,-1]	[-15,-1]	[-10,-1]	[-5,-1]	[-1,0]	0	[0,1]	[1,5]	[1,10]	[1.15]	[1,20]	[-20,20]
QspreadADR	High5%	0.1043	0.1050	0.1060	0.1086	0.1538	0.1913	0.1530	0.1078	0.1061	0.1051	0.1043	0.2078
QspreadETF	High5%	0.0276	0.0277	0.0278	0.0277	0.0261	0.0249	0.0265	0.0280	0.0277	0.0278	0.0278	0.0540
QspreadCEF	High5%	0.0424	0.0426	0.0428	0.0428	0.0394	0.0362	0.0394	0.0432	0.0431	0.0428	0.0427	0.0828
QspreadADR	Low5%	0.0948	0.0941	0.0931	0.0909	0.0462	0.0083	0.0466	0.0910	0.0929	0.0940	0.0947	0.1809
QspreadETF	Low5%	0.0298	0.0297	0.0296	0.0297	0.0318	0.0336	0.0321	0.0295	0.0295	0.0296	0.0297	0.0583
QspreadCEF	Low5%	0.0425	0.0423	0.0422	0.0422	0.0454	0.0482	0.0455	0.0421	0.0420	0.0421	0.0423	0.0830

(b) Average Qspread of ADR, ETF, and CEF Around the Buys of ETF

Variable		[-20,-1]	[-15,-1]	[-10,-1]	[-5,-1]	[-1,0]	0	[0,1]	[1,5]	[1,10]	[1.15]	[1,20]	[-20,20]
QspreadETF	High5%	0.0816	0.0831	0.0853	0.0896	0.1955	0.2906	0.1944	0.0878	0.0840	0.0821	0.0809	0.1686
QspreadADR	High5%	0.0775	0.0774	0.0777	0.0776	0.0721	0.0670	0.0716	0.0777	0.0783	0.0778	0.0778	0.1511
QspreadCEF	High5%	0.0702	0.0702	0.0703	0.0709	0.0667	0.0600	0.0650	0.0702	0.0698	0.0693	0.0692	0.1357
QspreadETF	Low5%	0.0558	0.0552	0.0544	0.0529	0.0261	0.0031	0.0263	0.0530	0.0545	0.0552	0.0557	0.1064
QspreadADR	Low5%	0.0901	0.0901	0.0901	0.0901	0.0911	0.0918	0.0910	0.0900	0.0901	0.0901	0.0901	0.1760
QspreadCEF	Low5%	0.0592	0.0591	0.0591	0.0593	0.0635	0.0672	0.0635	0.0592	0.0591	0.0592	0.0593	0.1160

Table 3.13 (Continued)

(c) Average Qspread of ADR, ETF, and CEF Around the Buys of CEF

Variable		[-20,-1]	[-15,-1]	[-10,-1]	[-5,-1]	[-1,0]	0	[0,1]	[1,5]	[1,10]	[1.15]	[1,20]	[-20,20]
QspreadCEF	High5%	0.0769	0.0791	0.0818	0.0866	0.2169	0.3305	0.2124	0.0831	0.0788	0.0763	0.0752	0.1606
QspreadADR	High5%	0.1060	0.1063	0.1061	0.1064	0.0937	0.0803	0.0928	0.1063	0.1066	0.1061	0.1057	0.2054
QspreadETF	High5%	0.0644	0.0642	0.0641	0.0647	0.0567	0.0487	0.0556	0.0649	0.0650	0.0650	0.0646	0.1252
QspreadCEF	Low5%	0.0523	0.0519	0.0513	0.0503	0.0266	0.0060	0.0268	0.0503	0.0514	0.0519	0.0523	0.0999
QspreadADR	Low5%	0.1003	0.1003	0.1003	0.1003	0.1014	0.1025	0.1014	0.1002	0.1002	0.1002	0.1003	0.1959
QspreadETF	Low5%	0.0659	0.0658	0.0658	0.0658	0.0673	0.0687	0.0673	0.0657	0.0658	0.0658	0.0659	0.1288

(d) Compare Qspreads among ADR, ETF, and CEF aroung the largest and smallest trades

Price		K=-20	-10	-5	0	5	10	20
ADR	High 5%	0.1084	0.1138	0.1223	0.1913	0.1217	0.1138	0.1084
	Low 5%	0.0907	0.0854	0.0772	0.0083	0.0772	0.0852	0.0906
	Difference	0.0177	0.0284	0.0452	0.1830	0.0445	0.0286	0.0179
ETF	High 5%	0.0916	0.1040	0.1231	0.2906	0.1216	0.1027	0.0909
	Low 5%	0.0533	0.0498	0.0446	0.0031	0.0447	0.0498	0.0533
	Difference	0.0383	0.0542	0.0785	0.2874	0.0769	0.0529	0.0376
CEF	High 5%	0.0889	0.1044	0.1273	0.3305	0.1243	0.1017	0.0874
	Low 5%	0.0501	0.0472	0.0429	0.0060	0.0429	0.0472	0.0501
	Difference	0.0389	0.0572	0.0844	0.3245	0.0814	0.0545	0.0373
ADR-ETF	High 5%	0.0168	0.0098	-0.0008	-0.0993	0.0001	0.0111	0.0175
	Low 5%	0.0374	0.0356	0.0325	0.0051	0.0324	0.0353	0.0373
ETF-CEF	High 5%	0.0026	-0.0004	-0.0042	-0.0400	-0.0027	0.0011	0.0035
	Low 5%	0.0032	0.0025	0.0017	-0.0028	0.0018	0.0026	0.0032
ADR-CEF	High 5%	0.0195	0.0094	-0.0049	-0.1393	-0.0026	0.0121	0.0211
	Low 5%	0.0406	0.0381	0.0343	0.0023	0.0342	0.0380	0.0405

Panel C: Average Qspread Around the Largest v.s. Smallest Sells

(a) Average Qspread of ADR, ETF, and CEF Around the Sells of ADR

Variable		[-20,-1]	[-15,-1]	[-10,-1]	[-5,-1]	[-1,0]	0	[0,1]	[1,5]	[1,10]	[1.15]	[1,20]	[-20,20]
QspreadADR	High5%	0.1041	0.1048	0.1060	0.1089	0.1640	0.2100	0.1634	0.1084	0.1053	0.1039	0.1030	0.2073
QspreadETF	High5%	0.0247	0.0247	0.0249	0.0251	0.0232	0.0214	0.0240	0.0252	0.0245	0.0245	0.0242	0.0476
QspreadCEF	High5%	0.0426	0.0427	0.0429	0.0429	0.0387	0.0345	0.0378	0.0428	0.0427	0.0427	0.0427	0.0828
QspreadADR	Low5%	0.0902	0.0894	0.0883	0.0862	0.0426	0.0058	0.0428	0.0858	0.0880	0.0891	0.0898	0.1717
QspreadETF	Low5%	0.0243	0.0242	0.0242	0.0242	0.0256	0.0267	0.0257	0.0241	0.0242	0.0242	0.0243	0.0476
QspreadCEF	Low5%	0.0422	0.0420	0.0418	0.0418	0.0447	0.0473	0.0450	0.0418	0.0418	0.0418	0.0420	0.0825

Table 3.13 (Continued)

(b) Average Qspread of ADR, ETF, and CEF Around the Sells of ETF

Variable		[-20,-1]	[-15,-1]	[-10,-1]	[-5,-1]	[-1,0]	0	[0,1]	[1,5]	[1,10]	[1.15]	[1,20]	[-20,20]
QspreadETF	High5%	0.0679	0.0701	0.0730	0.0775	0.2002	0.3059	0.1965	0.0756	0.0702	0.0676	0.0658	0.1420
QspreadADR	High5%	0.0741	0.0739	0.0736	0.0729	0.0694	0.0637	0.0688	0.0748	0.0752	0.0746	0.0741	0.1442
QspreadCEF	High5%	0.0565	0.0566	0.0569	0.0578	0.0538	0.0502	0.0544	0.0569	0.0569	0.0567	0.0568	0.1103
QspreadETF	Low5%	0.0426	0.0421	0.0415	0.0403	0.0191	0.0012	0.0191	0.0401	0.0414	0.0420	0.0425	0.0811
QspreadADR	Low5%	0.0859	0.0859	0.0859	0.0859	0.0866	0.0873	0.0866	0.0859	0.0858	0.0859	0.0859	0.1678
QspreadCEF	Low5%	0.0515	0.0514	0.0513	0.0512	0.0527	0.0542	0.0526	0.0513	0.0514	0.0515	0.0516	0.1006

(c) Average Qspread of ADR, ETF, and CEF Around the Sells of CEF

Variable		[-20,-1]	[-15,-1]	[-10,-1]	[-5,-1]	[-1,0]	0	[0,1]	[1,5]	[1,10]	[1.15]	[1,20]	[-20,20]
QspreadCEF	High5%	0.0676	0.0696	0.0725	0.0792	0.2137	0.3329	0.2121	0.0751	0.0699	0.0675	0.0664	0.1432
QspreadADR	High5%	0.1057	0.1059	0.1055	0.1050	0.0927	0.0841	0.0944	0.1058	0.1058	0.1055	0.1055	0.2051
QspreadETF	High5%	0.0439	0.0443	0.0445	0.0456	0.0424	0.0389	0.0426	0.0453	0.0451	0.0451	0.0447	0.0863
QspreadCEF	Low5%	0.0461	0.0458	0.0453	0.0444	0.0229	0.0041	0.0230	0.0444	0.0452	0.0457	0.0460	0.0879
QspreadADR	Low5%	0.0980	0.0980	0.0979	0.0980	0.0992	0.1003	0.0992	0.0979	0.0979	0.0979	0.0980	0.1914
QspreadETF	Low5%	0.0504	0.0504	0.0503	0.0503	0.0511	0.0519	0.0510	0.0501	0.0502	0.0502	0.0503	0.0984

(d) Compare Qspreads among ADR, ETF, and CEF aroung the largest and smallest trades

Price		K=-20	-10	-5	0	5	10	20
ADR	High 5%	0.1091	0.1155	0.1258	0.2100	0.1253	0.1148	0.1081
	Low 5%	0.0862	0.0808	0.0728	0.0058	0.0725	0.0805	0.0858
	Difference	0.0230	0.0346	0.0530	0.2042	0.0528	0.0343	0.0224
ETF	High 5%	0.0793	0.0942	0.1155	0.3059	0.1140	0.0916	0.0773
	Low 5%	0.0406	0.0378	0.0338	0.0012	0.0336	0.0377	0.0406
	Difference	0.0387	0.0564	0.0818	0.3047	0.0804	0.0539	0.0367
CEF	High 5%	0.0802	0.0961	0.1214	0.3329	0.1180	0.0938	0.0791
	Low 5%	0.0441	0.0415	0.0376	0.0041	0.0376	0.0414	0.0440
	Difference	0.0361	0.0546	0.0838	0.3288	0.0804	0.0523	0.0351
ADR-ETF	High 5%	0.0298	0.0213	0.0102	-0.0959	0.0113	0.0232	0.0309
	Low 5%	0.0456	0.0430	0.0390	0.0046	0.0389	0.0428	0.0452
ETF-CEF	High 5%	-0.0009	-0.0020	-0.0059	-0.0270	-0.0041	-0.0022	-0.0018
	Low 5%	-0.0035	-0.0037	-0.0039	-0.0029	-0.0040	-0.0037	-0.0034
ADR-CEF	High 5%	0.0289	0.0193	0.0043	-0.1229	0.0073	0.0210	0.0291
	Low 5%	0.0421	0.0393	0.0351	0.0017	0.0349	0.0391	0.0418

Table 3.14 Depth Around the Largest versus Smallest Trades by the Triplets (Leading ADR, ETF, and CEF)

This table presents analysis of depths around the largest v.s. smallest buying and selling activity of the three securities leading ADR, ETF, and CEF. For each security, I select the trades with the highest 5% and lowest 5% trading volume. All the trades are time-stamped in 5-minute interval. Depth is computed as (ask depth + bid depth)/2. Then I calculate the average depths of the three securities over windows [-k,-1], 0, [1, k], k=1, 5, 10, 15, 20, which presents the average depths just before and after the largest v.s. smallest trades of one security. I also show the average depths over windows [-k, 0], and [0, k], k=5, 10, 20. Panel A presents the average depths of leading ADR, ETF, and CEF around the largest v.s smallest trades of one security. Panel B presents the average depths of leading ADR, ETF, and CEF around the largest v.s smallest buying activities of one security. Panel C presents the average depths of leading ADR, ETF, and CEF around the largest v.s smallest selling activities of one security.

Panel A: Average Depth Around the Largest v.s. Smallest Trades

(a) Average Depth of ADR, ETF, and CEF Around the trades of ADR

Variable		[-20,-1]	[-15,-1]	[-10,-1]	[-5,-1]	[-1,0]	0	[0,1]	[1,5]	[1,10]	[1.15]	[1,20]	[-20,20]
DepthADR	High5%	49.664	49.398	48.599	45.613	59.620	61.240	56.666	52.557	52.332	52.085	51.838	52.088
DepthETF	High5%	19.739	19.402	18.725	17.015	18.892	17.592	18.891	20.317	20.455	20.523	20.519	20.540
DepthCEF	High5%	6.300	6.181	5.971	5.371	5.534	4.802	5.549	6.540	6.571	6.592	6.603	6.563
DepthADR	Low5%	25.603	25.192	24.388	22.202	23.846	21.474	24.401	27.335	27.354	27.401	27.453	26.979
DepthETF	Low5%	20.132	19.795	19.216	17.623	23.053	24.822	23.143	21.361	21.296	21.288	21.277	21.240
DepthCEF	Low5%	7.903	7.811	7.631	7.105	10.477	12.088	10.456	8.532	8.471	8.426	8.398	8.435

(b) Average Depth of ADR, ETF, and CEF Around the trades of ETF

Variable		[-20,-1]	[-15,-1]	[-10,-1]	[-5,-1]	[-1,0]	0	[0,1]	[1,5]	[1,10]	[1.15]	[1,20]	[-20,20]
DepthETF	High5%	37.545	37.479	37.200	35.479	64.701	82.719	63.446	41.760	40.426	39.639	39.003	40.269
DepthADR	High5%	23.377	22.979	22.125	20.210	23.460	22.586	23.240	23.953	24.103	24.121	24.148	24.302
DepthCEF	High5%	5.036	4.949	4.779	4.375	4.637	4.110	4.751	5.448	5.405	5.367	5.360	5.294
DepthETF	Low5%	20.612	20.194	19.466	17.683	14.498	8.386	14.409	21.174	21.414	21.571	21.690	21.328
DepthADR	Low5%	28.818	28.371	27.523	25.244	30.536	30.754	30.525	30.344	30.343	30.348	30.346	30.285
DepthCEF	Low5%	6.016	5.924	5.754	5.290	6.687	6.977	6.681	6.347	6.337	6.334	6.332	6.337

(c) Average Depth of ADR, ETF, and CEF Around the trades of CEF

Variable		[-20,-1]	[-15,-1]	[-10,-1]	[-5,-1]	[-1,0]	0	[0,1]	[1,5]	[1,10]	[1.15]	[1,20]	[-20,20]
DepthCEF	High5%	11.554	11.730	11.816	11.522	25.003	34.051	23.637	12.401	11.972	11.746	11.608	12.407
DepthADR	High5%	27.541	26.985	26.099	23.765	25.237	22.993	25.212	27.644	27.901	28.009	28.203	28.420
DepthETF	High5%	30.331	29.810	28.898	26.212	28.202	26.042	28.933	31.371	31.481	31.381	31.486	31.531
DepthCEF	Low5%	4.109	4.018	3.860	3.479	2.475	0.976	2.507	4.231	4.291	4.324	4.346	4.247
DepthADR	Low5%	26.108	25.712	24.948	22.899	27.979	28.392	27.987	27.557	27.545	27.534	27.521	27.469
DepthETF	Low5%	30.457	29.990	29.093	26.699	32.936	33.731	32.955	32.065	32.013	31.997	31.989	32.018

Table 3.14 (Continued)

(d) Compare Qspreads among ADR, ETF, and CEF aroung the largest and smallest trades

Price		K=-20	-10	-5	0	5	10	20
ADR	High 5%	52.5693	54.1504	55.7979	61.2397	54.0040	53.1418	52.2855
	Low 5%	26.6252	26.3403	25.7815	21.4741	26.2826	26.7434	27.0818
	Difference	25.9441	27.8101	30.0163	39.7656	27.7214	26.3984	25.2037
ETF	High 5%	41.4831	44.7194	49.2651	82.7190	48.5878	44.2720	41.0852
	Low 5%	21.0119	20.2281	19.0808	8.3862	18.9999	20.1910	21.0186
	Difference	20.4712	24.4912	30.1843	74.3328	29.5879	24.0809	20.0666
CEF	High 5%	13.1749	14.9110	17.1976	34.0507	16.0090	13.9791	12.6767
	Low 5%	4.1558	3.9486	3.6413	0.9759	3.6876	3.9874	4.1833
	Difference	9.0191	10.9625	13.5563	33.0747	12.3215	9.9917	8.4934
ADR-ETF	High 5%	11.0862	9.4310	6.5328	-21.4793	5.4162	8.8698	11.2002
	Low 5%	5.6133	6.1122	6.7008	13.0879	7.2827	6.5523	6.0632
ETF-CEF	High 5%	28.3082	29.8083	32.0674	48.6683	32.5788	30.2929	28.4085
	Low 5%	16.8561	16.2795	15.4394	7.4103	15.3123	16.2036	16.8353
ADR-CEF	High 5%	39.3944	39.2393	38.6002	27.1890	37.9950	39.1627	39.6087
	Low 5%	22.4694	22.3918	22.1402	20.4982	22.5950	22.7559	22.8985

Panel B: Average Depth Around the Largest v.s. Smallest Buys

(a) Average Depth of ADR, ETF, and CEF Around the Buys of ADR

Variable		[-20,-1]	[-15,-1]	[-10,-1]	[-5,-1]	[-1,0]	0	[0,1]	[1,5]	[1,10]	[1.15]	[1,20]	[-20,20]
DepthADR	High5%	22.772	22.744	22.590	21.769	38.275	46.643	36.302	24.689	24.150	23.814	23.601	24.294
DepthETF	High5%	11.154	10.947	10.562	9.709	10.892	10.304	10.985	11.581	11.548	11.634	11.713	11.673
DepthCEF	High5%	2.200	2.160	2.106	1.922	2.070	1.833	2.085	2.392	2.385	2.378	2.377	2.330
DepthADR	Low5%	12.112	11.794	11.248	9.985	5.866	1.072	5.880	12.076	12.460	12.660	12.804	12.469
DepthETF	Low5%	11.325	11.145	10.808	9.883	12.340	12.798	12.367	12.010	11.998	11.987	11.974	11.914
DepthCEF	Low5%	2.804	2.757	2.676	2.461	3.171	3.351	3.152	2.955	2.954	2.957	2.957	2.959

(b) Average Depth of ADR, ETF, and CEF Around the Buys of ETF

Variable		[-20,-1]	[-15,-1]	[-10,-1]	[-5,-1]	[-1,0]	0	[0,1]	[1,5]	[1,10]	[1.15]	[1,20]	[-20,20]
DepthETF	High5%	24.458	24.561	24.554	23.843	53.991	75.268	53.048	27.712	26.545	25.847	25.399	26.751
DepthADR	High5%	11.622	11.433	11.005	10.015	11.390	10.979	11.251	11.909	12.015	12.060	12.092	12.120
DepthCEF	High5%	2.545	2.475	2.383	2.186	2.373	2.280	2.636	2.706	2.739	2.734	2.722	2.687
DepthETF	Low5%	12.094	11.792	11.289	10.084	5.900	0.646	5.895	12.142	12.452	12.621	12.741	12.415
DepthADR	Low5%	13.452	13.240	12.843	11.779	14.182	14.215	14.171	14.139	14.153	14.158	14.162	14.144
DepthCEF	Low5%	2.401	2.362	2.291	2.107	2.619	2.691	2.614	2.526	2.526	2.524	2.525	2.526

Table 3.14 (Continued)

(c) Average Depth of ADR, ETF, and CEF Around the Buys of CEF

Variable		[-20,-1]	[-15,-1]	[-10,-1]	[-5,-1]	[-1,0]	0	[0,1]	[1,5]	[1,10]	[1.15]	[1,20]	[-20,20]
DepthCEF	High5%	5.571	5.797	6.071	6.361	22.433	33.835	20.977	6.831	6.182	5.792	5.583	6.399
DepthADR	High5%	13.094	12.889	12.491	11.392	12.141	10.927	11.630	12.668	12.736	12.720	12.785	13.210
DepthETF	High5%	19.091	18.651	18.124	16.748	17.648	16.029	17.485	19.520	19.751	19.817	19.829	19.844
DepthCEF	Low5%	1.948	1.901	1.818	1.619	0.992	0.206	0.997	1.946	2.001	2.031	2.050	2.002
DepthADR	Low5%	12.607	12.410	12.034	11.037	13.320	13.389	13.326	13.265	13.269	13.270	13.270	13.251
DepthETF	Low5%	16.910	16.650	16.148	14.806	18.014	18.226	18.013	17.784	17.766	17.758	17.757	17.762

(d) Compare Qspreads among ADR, ETF, and CEF aroung the largest and smallest trades

Price		K=-20	-10	-5	0	5	10	20
ADR	High 5%	24.9915	26.8300	29.5427	46.6432	28.3477	26.1945	24.6984
	Low 5%	12.1631	11.3450	10.1635	1.0716	10.2395	11.4202	12.2369
	Difference	12.8284	15.4850	19.3791	45.5716	18.1083	14.7744	12.4616
ETF	High 5%	28.0420	31.3962	36.3866	75.2677	35.6384	30.9743	27.7743
	Low 5%	12.1244	11.3479	10.1919	0.6459	10.1972	11.3538	12.1419
	Difference	15.9176	20.0483	26.1947	74.6218	25.4412	19.6206	15.6324
CEF	High 5%	7.1819	9.1468	12.0005	33.8346	11.3317	8.6959	6.9279
	Low 5%	1.9581	1.8366	1.6536	0.2060	1.6554	1.8370	1.9614
	Difference	5.2239	7.3103	10.3469	33.6286	9.6763	6.8589	4.9664
ADR-ETF	High 5%	-3.0505	-4.5662	-6.8439	-28.6245	-7.2907	-4.7798	-3.0758
	Low 5%	0.0387	-0.0029	-0.0284	0.4257	0.0422	0.0664	0.0950
ETF-CEF	High 5%	20.8601	22.2494	24.3861	41.4330	24.3067	22.2785	20.8464
	Low 5%	10.1663	9.5113	8.5383	0.4399	8.5418	9.5168	10.1804
ADR-CEF	High 5%	17.8096	17.6831	17.5422	12.8085	17.0160	17.4987	17.7706
	Low 5%	10.2050	9.5084	8.5099	0.8656	8.5841	9.5832	10.2754

Panel C: Average Depth Around the Largest v.s. Smallest Sells

(a) Average Depth of ADR, ETF, and CEF Around the Sells of ADR

Variable		[-20,-1]	[-15,-1]	[-10,-1]	[-5,-1]	[-1,0]	0	[0,1]	[1,5]	[1,10]	[1.15]	[1,20]	[-20,20]
DepthADR	High5%	21.661	21.713	21.579	20.691	36.427	44.490	34.791	23.594	22.967	22.586	22.361	22.942
DepthETF	High5%	7.440	7.334	7.151	6.608	7.339	6.865	7.512	7.881	7.965	7.929	7.866	7.814
DepthCEF	High5%	3.276	3.233	3.144	2.820	2.861	2.379	2.847	3.424	3.469	3.460	3.462	3.424
DepthADR	Low5%	11.423	11.123	10.611	9.395	5.331	0.739	5.340	11.338	11.752	11.957	12.092	11.754
DepthETF	Low5%	7.475	7.339	7.087	6.470	7.995	8.188	7.991	7.791	7.799	7.804	7.819	7.835
DepthCEF	Low5%	3.321	3.269	3.168	2.916	3.795	4.040	3.798	3.519	3.507	3.508	3.511	3.511

Table 3.14 (Continued)

(b) Average Depth of ADR, ETF, and CEF Around the Sells of ETF

Variable		[-20,-1]	[-15,-1]	[-10,-1]	[-5,-1]	[-1,0]	0	[0,1]	[1,5]	[1,10]	[1.15]	[1,20]	[-20,20]
DepthETF	High5%	15.612	15.804	15.968	15.810	45.905	68.509	44.804	18.010	16.851	16.293	15.802	17.369
DepthADR	High5%	10.266	10.081	9.811	8.982	10.935	10.472	10.635	10.642	10.590	10.538	10.509	10.641
DepthCEF	High5%	2.170	2.159	2.113	1.963	2.056	1.765	2.169	2.451	2.378	2.333	2.312	2.282
DepthETF	Low5%	8.037	7.833	7.495	6.682	3.782	0.218	3.777	8.005	8.217	8.332	8.416	8.226
DepthADR	Low5%	12.820	12.620	12.239	11.220	13.491	13.521	13.496	13.496	13.495	13.500	13.501	13.467
DepthCEF	Low5%	2.881	2.835	2.750	2.522	3.075	3.120	3.076	3.030	3.030	3.032	3.033	3.030

(c) Average Depth of ADR, ETF, and CEF Around the Sells of CEF

Variable		[-20,-1]	[-15,-1]	[-10,-1]	[-5,-1]	[-1,0]	0	[0,1]	[1,5]	[1,10]	[1.15]	[1,20]	[-20,20]
DepthCEF	High5%	6.523	6.717	6.951	7.232	22.421	33.674	21.189	7.216	6.801	6.565	6.433	7.299
DepthADR	High5%	12.476	12.260	11.876	10.926	11.686	10.789	12.102	12.704	12.739	12.847	12.887	12.931
DepthETF	High5%	11.819	11.640	11.262	10.248	10.759	9.935	11.401	12.408	12.366	12.369	12.486	12.384
DepthCEF	Low5%	2.217	2.165	2.073	1.852	1.183	0.306	1.189	2.239	2.295	2.322	2.338	2.283
DepthADR	Low5%	11.157	10.985	10.655	9.773	11.825	11.903	11.821	11.737	11.741	11.742	11.740	11.721
DepthETF	Low5%	11.702	11.515	11.161	10.226	12.411	12.557	12.427	12.286	12.284	12.282	12.282	12.290

(d) Compare Qspreads among ADR, ETF, and CEF aroung the largest and smallest trades

Price		K=-20	-10	-5	0	5	10	20
ADR	High 5%	23.7650	25.6018	28.0759	44.4904	27.0770	24.9237	23.4150
	Low 5%	11.4586	10.6784	9.5183	0.7386	9.5537	10.7338	11.5310
	Difference	12.3065	14.9235	18.5576	43.7518	17.5233	14.1899	11.8839
ETF	High 5%	18.8750	22.1963	27.2278	68.5086	26.4284	21.5488	18.3131
	Low 5%	8.0474	7.5149	6.7183	0.2182	6.7042	7.4873	8.0225
	Difference	10.8276	14.6814	20.5096	68.2904	19.7243	14.0614	10.2907
CEF	High 5%	8.1261	10.0128	12.8445	33.6738	11.6254	9.2439	7.7303
	Low 5%	2.2312	2.1009	1.9027	0.3063	1.9166	2.1132	2.2406
	Difference	5.8949	7.9119	10.9418	33.3676	9.7088	7.1307	5.4897
ADR-ETF	High 5%	4.8901	3.4055	0.8481	-24.0182	0.6485	3.3749	5.1018
	Low 5%	3.4112	3.1635	2.8001	0.5204	2.8495	3.2465	3.5086
ETF-CEF	High 5%	10.7489	12.1835	14.3833	34.8347	14.8030	12.3049	10.5828
	Low 5%	5.8162	5.4140	4.8155	-0.0881	4.7876	5.3741	5.7818
ADR-CEF	High 5%	15.6390	15.5890	15.2314	10.8165	15.4516	15.6798	15.6846
	Low 5%	9.2274	8.5775	7.6156	0.4323	7.6371	8.6206	9.2904

Table 3.15 Return Volatility Around the Largest versus Smallest Trades by the Triplets (Leading ADR, ETF, and CEF)

This table presents analysis of return volatilities around the largest v.s. smallest buying and selling activity of the three securities leading ADR, ETF, and CEF. For each security, I select the trades with the highest 5% and lowest 5% trading volume. All the trades are time-stamped in 5-minute interval. Return volatility is computed as absolute value of the midquote return. Then I calculate the average return volatilities of the three securities over windows [-k,-1], 0, [1, k], k=1, 5, 10, 15, 20, which presents the average return volatilities just before and after the largest v.s. smallest trades of one security. I also show the average return volatilities over windows [-k, 0], and [0, k], k=5, 10, 20. Panel A presents the average return volatilities of leading ADR, ETF, and CEF around the largest v.s smallest trades of one security. Panel B presents the average return volatilities of leading ADR, ETF, and CEF around the largest v.s smallest buying activities of one security. Panel C presents the average return volatilities of leading ADR, ETF, and CEF around the largest v.s smallest selling activities of one security.

Panel A: Average Return Volatility Around the Largest v.s. Smallest Trades

(a) Average Return Volatility of ADR, ETF, and CEF Around the trades of ADR

Variable		[-20,-1]	[-15,-1]	[-10,-1]	[-5,-1]	[-1,0]	0	[0,1]	[1,5]	[1,10]	[1.15]	[1,20]	[-20,20]
VolatADR	High5%	0.0199	0.0200	0.0203	0.0204	0.0234	0.0257	0.0238	0.0205	0.0200	0.0198	0.0197	0.0200
VolatETF	High5%	0.0067	0.0068	0.0070	0.0074	0.0070	0.0061	0.0071	0.0073	0.0071	0.0069	0.0068	0.0065
VolatCEF	High5%	0.0131	0.0132	0.0133	0.0134	0.0112	0.0095	0.0113	0.0135	0.0134	0.0133	0.0133	0.0131
VolatADR	Low5%	0.0149	0.0148	0.0147	0.0145	0.0127	0.0110	0.0130	0.0155	0.0152	0.0151	0.0152	0.0147
VolatETF	Low5%	0.0066	0.0066	0.0065	0.0065	0.0076	0.0086	0.0076	0.0066	0.0065	0.0065	0.0066	0.0066
VolatCEF	Low5%	0.0125	0.0124	0.0124	0.0124	0.0162	0.0195	0.0160	0.0125	0.0124	0.0124	0.0125	0.0125

(b) Average Return Volatility of ADR, ETF, and CEF Around the trades of ETF

Variable		[-20,-1]	[-15,-1]	[-10,-1]	[-5,-1]	[-1,0]	0	[0,1]	[1,5]	[1,10]	[1.15]	[1,20]	[-20,20]
VolatETF	High5%	0.0118	0.0120	0.0122	0.0127	0.0242	0.0346	0.0238	0.0117	0.0115	0.0114	0.0113	0.0121
VolatADR	High5%	0.0115	0.0115	0.0115	0.0114	0.0105	0.0097	0.0110	0.0117	0.0116	0.0116	0.0115	0.0115
VolatCEF	High5%	0.0135	0.0136	0.0137	0.0139	0.0122	0.0110	0.0125	0.0137	0.0137	0.0135	0.0134	0.0134
VolatETF	Low5%	0.0084	0.0084	0.0083	0.0082	0.0057	0.0033	0.0060	0.0087	0.0086	0.0086	0.0086	0.0083
VolatADR	Low5%	0.0150	0.0150	0.0151	0.0151	0.0161	0.0170	0.0160	0.0151	0.0150	0.0150	0.0150	0.0150
VolatCEF	Low5%	0.0136	0.0135	0.0136	0.0137	0.0151	0.0163	0.0150	0.0144	0.0141	0.0140	0.0139	0.0136

(c) Average Return Volatility of ADR, ETF, and CEF Around the trades of CEF

Variable		[-20,-1]	[-15,-1]	[-10,-1]	[-5,-1]	[-1,0]	0	[0,1]	[1,5]	[1,10]	[1.15]	[1,20]	[-20,20]
VolatCEF	High5%	0.0187	0.0190	0.0197	0.0210	0.0431	0.0622	0.0425	0.0204	0.0195	0.0190	0.0185	0.0196
VolatADR	High5%	0.0163	0.0163	0.0164	0.0167	0.0136	0.0113	0.0146	0.0170	0.0165	0.0163	0.0163	0.0162
VolatETF	High5%	0.0087	0.0088	0.0089	0.0089	0.0080	0.0069	0.0084	0.0093	0.0090	0.0089	0.0088	0.0087
VolatCEF	Low5%	0.0120	0.0119	0.0118	0.0116	0.0069	0.0028	0.0072	0.0121	0.0121	0.0121	0.0122	0.0118
VolatADR	Low5%	0.0158	0.0158	0.0158	0.0158	0.0164	0.0169	0.0162	0.0159	0.0159	0.0159	0.0159	0.0158
VolatETF	Low5%	0.0084	0.0084	0.0083	0.0084	0.0087	0.0091	0.0086	0.0084	0.0084	0.0084	0.0084	0.0084

Table 3.15 (Continued)

(d) Compare Volatilitis among ADR, ETF, and CEF aroung the largest and smallest trades

Price		K=-20	-10	-5	0	5	10	20
ADR	High 5%	0.0202	0.0208	0.0213	0.0257	0.0214	0.0205	0.0200
	Low 5%	0.0147	0.0143	0.0139	0.0110	0.0141	0.0144	0.0146
	Difference	0.0055	0.0064	0.0074	0.0147	0.0073	0.0061	0.0054
ETF	High 5%	0.0129	0.0143	0.0164	0.0346	0.0155	0.0136	0.0124
	Low 5%	0.0082	0.0079	0.0074	0.0033	0.0076	0.0080	0.0082
	Difference	0.0047	0.0064	0.0090	0.0313	0.0079	0.0056	0.0042
CEF	High 5%	0.0207	0.0235	0.0278	0.0622	0.0274	0.0234	0.0206
	Low 5%	0.0115	0.0110	0.0101	0.0028	0.0103	0.0111	0.0116
	Difference	0.0092	0.0126	0.0177	0.0593	0.0171	0.0124	0.0090
ADR-ETF	High 5%	0.0073	0.0065	0.0050	-0.0089	0.0058	0.0069	0.0076
	Low 5%	0.0065	0.0065	0.0066	0.0077	0.0065	0.0064	0.0064
ETF-CEF	High 5%	-0.0078	-0.0093	-0.0115	-0.0276	-0.0119	-0.0098	-0.0082
	Low 5%	-0.0033	-0.0031	-0.0027	0.0005	-0.0027	-0.0031	-0.0033
ADR-CEF	High 5%	-0.0006	-0.0028	-0.0065	-0.0365	-0.0060	-0.0029	-0.0006
	Low 5%	0.0032	0.0034	0.0038	0.0082	0.0038	0.0033	0.0031

Panel B: Average Return Volatility Around the Largest v.s. Smallest Buys

(a) Average Return Volatility of ADR, ETF, and CEF Around the Buys of ADR

Variable		[-20,-1]	[-15,-1]	[-10,-1]	[-5,-1]	[-1,0]	0	[0,1]	[1,5]	[1,10]	[1.15]	[1,20]	[-20,20]
VolatADR	High5%	0.0093	0.0094	0.0096	0.0099	0.0154	0.0200	0.0146	0.0092	0.0092	0.0091	0.0091	0.0095
VolatETF	High5%	0.0032	0.0032	0.0032	0.0033	0.0029	0.0026	0.0031	0.0033	0.0033	0.0033	0.0032	0.0032
VolatCEF	High5%	0.0058	0.0058	0.0058	0.0058	0.0052	0.0047	0.0053	0.0061	0.0060	0.0059	0.0059	0.0058
VolatADR	Low5%	0.0071	0.0071	0.0070	0.0069	0.0036	0.0008	0.0042	0.0074	0.0073	0.0073	0.0073	0.0070
VolatETF	Low5%	0.0034	0.0034	0.0033	0.0033	0.0036	0.0038	0.0036	0.0033	0.0033	0.0033	0.0033	0.0034
VolatCEF	Low5%	0.0053	0.0052	0.0052	0.0052	0.0058	0.0063	0.0058	0.0053	0.0052	0.0052	0.0052	0.0053

(b) Average Return Volatility of ADR, ETF, and CEF Around the Buys of ETF

Variable		[-20,-1]	[-15,-1]	[-10,-1]	[-5,-1]	[-1,0]	0	[0,1]	[1,5]	[1,10]	[1.15]	[1,20]	[-20,20]
VolatETF	High5%	0.0064	0.0066	0.0068	0.0072	0.0186	0.0289	0.0175	0.0061	0.0061	0.0060	0.0060	0.0068
VolatADR	High5%	0.0054	0.0054	0.0054	0.0054	0.0050	0.0046	0.0051	0.0056	0.0055	0.0055	0.0055	0.0054
VolatCEF	High5%	0.0067	0.0067	0.0067	0.0067	0.0061	0.0053	0.0062	0.0068	0.0068	0.0066	0.0066	0.0066
VolatETF	Low5%	0.0043	0.0043	0.0042	0.0041	0.0021	0.0003	0.0024	0.0044	0.0044	0.0044	0.0044	0.0042
VolatADR	Low5%	0.0066	0.0066	0.0066	0.0067	0.0068	0.0069	0.0068	0.0067	0.0067	0.0067	0.0067	0.0066
VolatCEF	Low5%	0.0061	0.0061	0.0061	0.0061	0.0065	0.0068	0.0065	0.0063	0.0062	0.0062	0.0062	0.0061

Table 3.15 (Continued)

(c) Average Return Volatility of ADR, ETF, and CEF Around the Buys of CEF

Variable		[-20,-1]	[-15,-1]	[-10,-1]	[-5,-1]	[-1,0]	0	[0,1]	[1,5]	[1,10]	[1.15]	[1,20]	[-20,20]
VolatCEF	High5%	0.0091	0.0094	0.0099	0.0110	0.0354	0.0569	0.0327	0.0087	0.0086	0.0085	0.0083	0.0099
VolatADR	High5%	0.0075	0.0075	0.0075	0.0076	0.0064	0.0053	0.0069	0.0078	0.0077	0.0075	0.0075	0.0074
VolatETF	High5%	0.0047	0.0047	0.0048	0.0049	0.0044	0.0039	0.0045	0.0052	0.0049	0.0048	0.0048	0.0047
VolatCEF	Low5%	0.0057	0.0056	0.0056	0.0055	0.0030	0.0008	0.0032	0.0058	0.0057	0.0058	0.0058	0.0056
VolatADR	Low5%	0.0074	0.0074	0.0074	0.0074	0.0075	0.0076	0.0075	0.0074	0.0074	0.0074	0.0074	0.0074
VolatETF	Low5%	0.0043	0.0043	0.0043	0.0043	0.0044	0.0045	0.0044	0.0043	0.0043	0.0043	0.0043	0.0043

(d) Compare Volatilitis among ADR, ETF, and CEF aroung the largest and smallest trades

Price		K=-20	-10	-5	0	5	10	20
ADR	High 5%	0.0098	0.0105	0.0116	0.0200	0.0110	0.0101	0.0096
	Low 5%	0.0068	0.0065	0.0059	0.0008	0.0061	0.0066	0.0069
	Difference	0.0030	0.0041	0.0057	0.0192	0.0049	0.0036	0.0027
ETF	High 5%	0.0075	0.0088	0.0108	0.0289	0.0099	0.0082	0.0071
	Low 5%	0.0041	0.0039	0.0035	0.0003	0.0037	0.0040	0.0042
	Difference	0.0034	0.0050	0.0073	0.0286	0.0062	0.0042	0.0029
CEF	High 5%	0.0113	0.0141	0.0186	0.0569	0.0167	0.0130	0.0106
	Low 5%	0.0054	0.0052	0.0047	0.0008	0.0049	0.0052	0.0055
	Difference	0.0059	0.0090	0.0139	0.0561	0.0119	0.0078	0.0051
ADR-ETF	High 5%	0.0023	0.0017	0.0008	-0.0088	0.0011	0.0020	0.0025
	Low 5%	0.0027	0.0026	0.0024	0.0005	0.0024	0.0026	0.0027
ETF-CEF	High 5%	-0.0038	-0.0053	-0.0078	-0.0280	-0.0068	-0.0048	-0.0036
	Low 5%	-0.0013	-0.0013	-0.0012	-0.0005	-0.0012	-0.0013	-0.0013
ADR-CEF	High 5%	-0.0015	-0.0036	-0.0070	-0.0369	-0.0057	-0.0029	-0.0010
	Low 5%	0.0014	0.0013	0.0012	0.0001	0.0012	0.0013	0.0014

Panel C: Average Return Volatility Around the Largest v.s. Smallest Sells

(a) Average Return Volatility of ADR, ETF, and CEF Around the Sells of ADR

Variable		[-20,-1]	[-15,-1]	[-10,-1]	[-5,-1]	[-1,0]	0	[0,1]	[1,5]	[1,10]	[1.15]	[1,20]	[-20,20]
VolatADR	High5%	0.0103	0.0104	0.0106	0.0110	0.0177	0.0234	0.0169	0.0104	0.0103	0.0101	0.0100	0.0105
VolatETF	High5%	0.0032	0.0032	0.0035	0.0039	0.0051	0.0042	0.0047	0.0043	0.0039	0.0037	0.0035	0.0031
VolatCEF	High5%	0.0066	0.0066	0.0066	0.0066	0.0056	0.0048	0.0056	0.0067	0.0067	0.0067	0.0067	0.0066
VolatADR	Low5%	0.0067	0.0067	0.0066	0.0064	0.0033	0.0005	0.0037	0.0067	0.0067	0.0068	0.0068	0.0066
VolatETF	Low5%	0.0030	0.0030	0.0030	0.0030	0.0031	0.0033	0.0031	0.0030	0.0030	0.0030	0.0030	0.0030
VolatCEF	Low5%	0.0059	0.0059	0.0059	0.0059	0.0064	0.0069	0.0064	0.0059	0.0059	0.0059	0.0059	0.0059

Table 3.15 (Continued)

(b) Average Return Volatility of ADR, ETF, and CEF Around the Sells of ETF

Variable		[-20,-1]	[-15,-1]	[-10,-1]	[-5,-1]	[-1,0]	0	[0,1]	[1,5]	[1,10]	[1.15]	[1,20]	[-20,20]
VolatETF	High5%	0.0060	0.0061	0.0063	0.0067	0.0209	0.0336	0.0198	0.0059	0.0057	0.0056	0.0056	0.0064
VolatADR	High5%	0.0056	0.0055	0.0055	0.0055	0.0051	0.0049	0.0056	0.0059	0.0058	0.0057	0.0057	0.0056
VolatCEF	High5%	0.0065	0.0066	0.0066	0.0067	0.0061	0.0055	0.0061	0.0067	0.0068	0.0066	0.0065	0.0065
VolatETF	Low5%	0.0037	0.0037	0.0037	0.0036	0.0017	0.0001	0.0019	0.0038	0.0038	0.0038	0.0038	0.0036
VolatADR	Low5%	0.0066	0.0066	0.0066	0.0066	0.0067	0.0069	0.0067	0.0066	0.0066	0.0066	0.0066	0.0066
VolatCEF	Low5%	0.0063	0.0063	0.0063	0.0063	0.0066	0.0068	0.0066	0.0067	0.0065	0.0065	0.0065	0.0063

(c) Average Return Volatility of ADR, ETF, and CEF Around the Sells of CEF

Variable		[-20,-1]	[-15,-1]	[-10,-1]	[-5,-1]	[-1,0]	0	[0,1]	[1,5]	[1,10]	[1.15]	[1,20]	[-20,20]
VolatCEF	High5%	0.0107	0.0111	0.0117	0.0133	0.0400	0.0641	0.0376	0.0110	0.0107	0.0104	0.0102	0.0117
VolatADR	High5%	0.0077	0.0077	0.0077	0.0078	0.0063	0.0055	0.0068	0.0078	0.0076	0.0075	0.0076	0.0076
VolatETF	High5%	0.0039	0.0039	0.0040	0.0039	0.0036	0.0032	0.0039	0.0042	0.0041	0.0041	0.0040	0.0040
VolatCEF	Low5%	0.0059	0.0058	0.0058	0.0057	0.0030	0.0006	0.0033	0.0060	0.0060	0.0060	0.0060	0.0057
VolatADR	Low5%	0.0072	0.0072	0.0072	0.0072	0.0073	0.0074	0.0073	0.0072	0.0072	0.0072	0.0072	0.0072
VolatETF	Low5%	0.0038	0.0038	0.0038	0.0037	0.0038	0.0039	0.0038	0.0037	0.0037	0.0037	0.0038	0.0038

(d) Compare Volatilitis among ADR, ETF, and CEF aroung the largest and smallest trades

Price		K=-20	-10	-5	0	5	10	20
ADR	High 5%	0.0109	0.0118	0.0130	0.0234	0.0126	0.0115	0.0107
	Low 5%	0.0064	0.0060	0.0055	0.0005	0.0056	0.0061	0.0065
	Difference	0.0045	0.0057	0.0076	0.0229	0.0070	0.0053	0.0042
ETF	High 5%	0.0073	0.0088	0.0112	0.0336	0.0105	0.0083	0.0069
	Low 5%	0.0036	0.0033	0.0030	0.0001	0.0031	0.0034	0.0036
	Difference	0.0037	0.0054	0.0082	0.0335	0.0074	0.0049	0.0033
CEF	High 5%	0.0133	0.0164	0.0217	0.0641	0.0198	0.0155	0.0128
	Low 5%	0.0056	0.0053	0.0048	0.0006	0.0050	0.0054	0.0056
	Difference	0.0076	0.0111	0.0169	0.0635	0.0149	0.0101	0.0072
ADR-ETF	High 5%	0.0036	0.0030	0.0019	-0.0102	0.0021	0.0032	0.0038
	Low 5%	0.0029	0.0027	0.0025	0.0004	0.0025	0.0027	0.0029
ETF-CEF	High 5%	-0.0060	-0.0077	-0.0106	-0.0305	-0.0094	-0.0073	-0.0059
	Low 5%	-0.0021	-0.0020	-0.0018	-0.0005	-0.0019	-0.0020	-0.0021
ADR-CEF	High 5%	-0.0023	-0.0047	-0.0087	-0.0407	-0.0073	-0.0041	-0.0021
	Low 5%	0.0008	0.0007	0.0006	-0.0001	0.0006	0.0007	0.0008

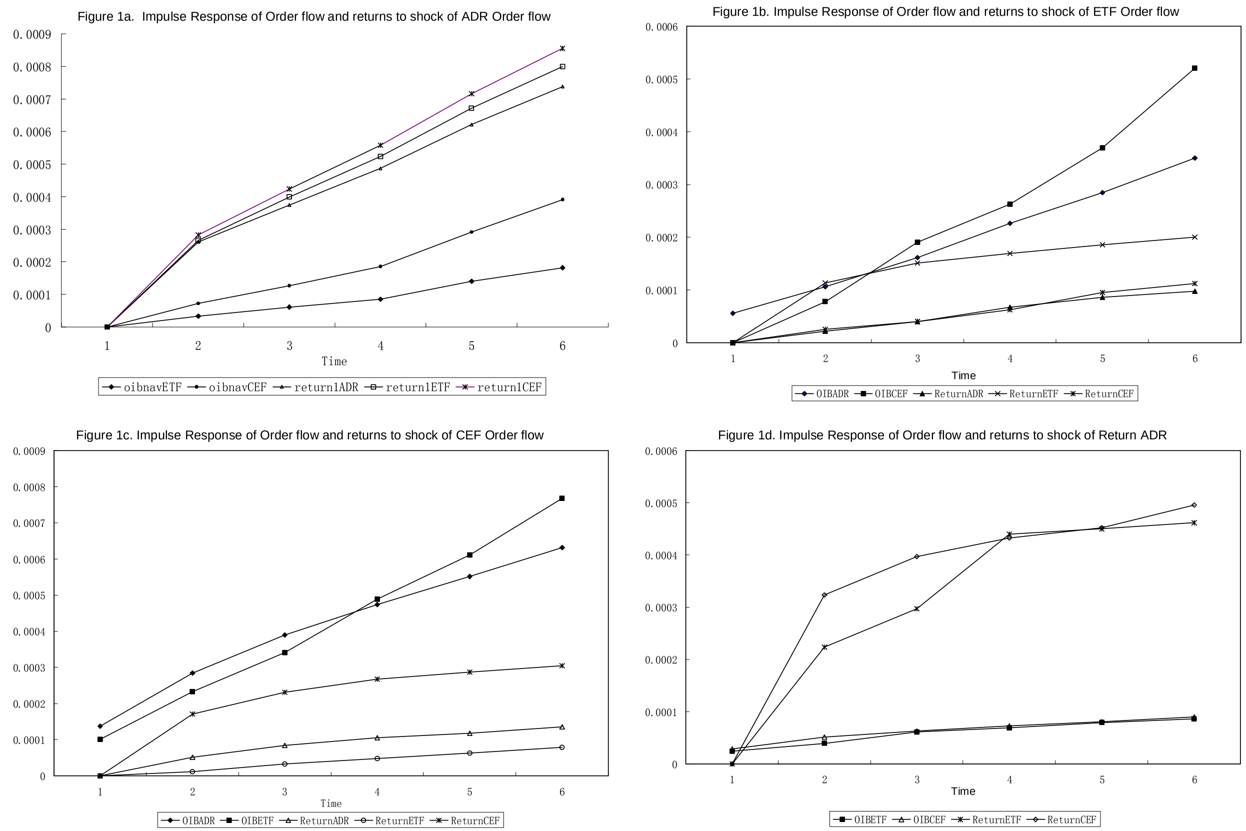
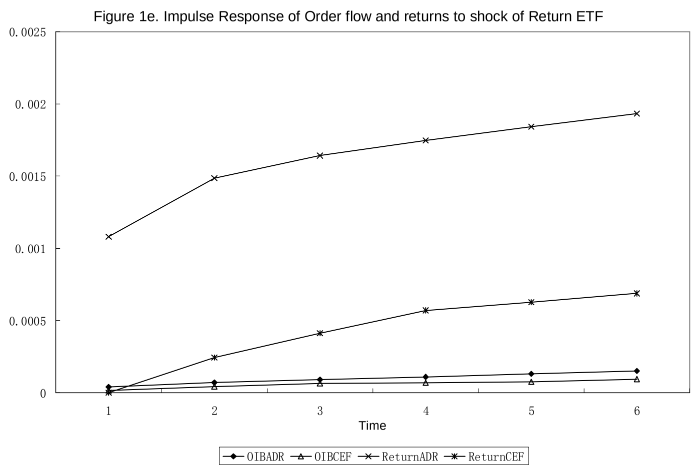


Figure 3.1 Impulse Response of Order flow and returns to shock of innovations



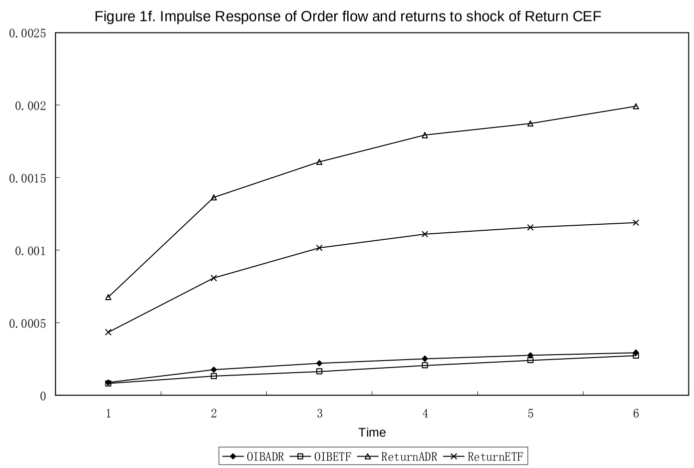


Figure 3.1 (Continued)

This Figure presents the Impulse Response of Order flow and returns to shock of innovations. I define the price-setting buys and sells by using the algorithm developed by Lee and Ready (1991). For each 5 minute interval for all the three securities across the countries, I compute "price-setting" order imbalances by security type by subtracting the price-setting sell volume from the price-setting buy volume, and then normalizing by the stock's average 5-minute price-setting volume over the sample period. Vector Y_t can be expressed in terms of current and lagged innovations: $Y_t=A_t+\sum A_j Y_{t-j}+u_t$, where $Y_t=\{OIB_t^1, OIB_t^2, OIB_t^3, R_t^1, R_t^2, R_t^3\}$ represents net order imbalances and returns of the leading ADR, ETF, and CEF respectively. The lag length is chosen as k=6 by Akaike and Schwartz-Bayes criteria. Figure 1a-1f show the Impulse Response of Order flow and Returns to shock of innovations when the shocks are from OIBADR, OIBETF, OIBCEF, ReturnADR, ReturnETF, and ReturnCEF.

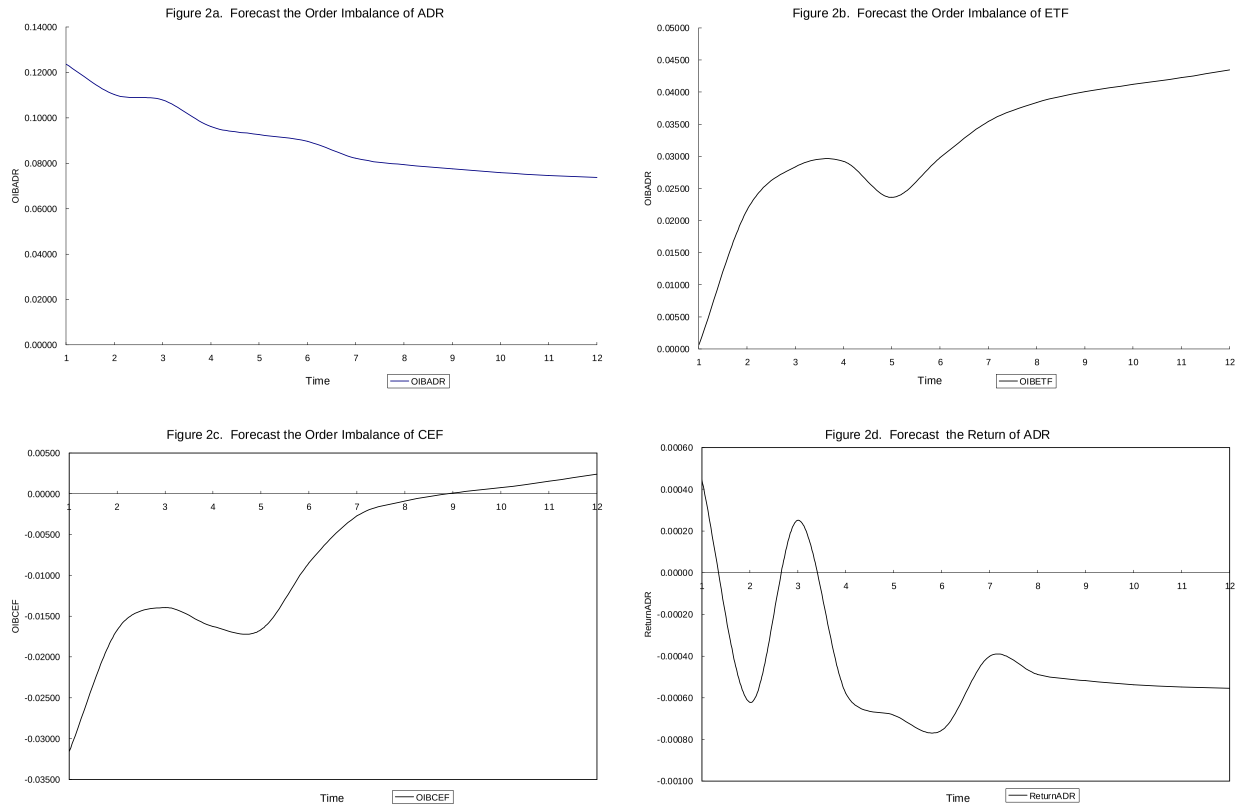
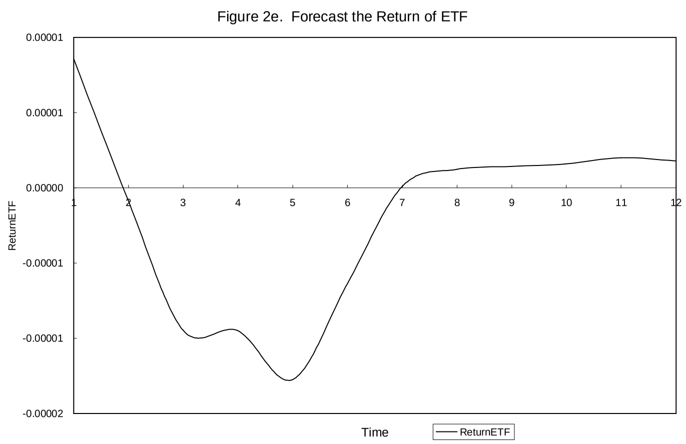


Figure 3.2 Forecasting the Order flow and returns of ADR, ETF, and CEF



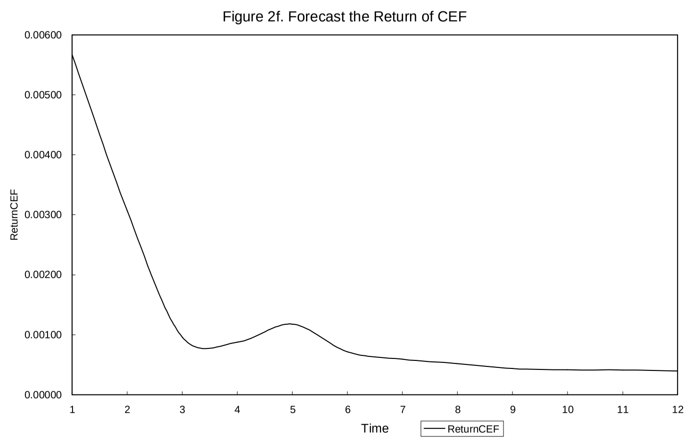


Figure 3.2 (Continued)

This Figure presents the forecast of Order flow and returns of ADR, ETF, and CEF. I define the price-setting buys and sells by using the algorithm developed by Lee and Ready (1991). For each 5 minute interval for all the three securities across the countries, I compute "price-setting" order imbalances by security type by subtracting the price-setting sell volume from the price-setting buy volume, and then normalizing by the stock's average 5-minute price-setting volume over the sample period. Vector Y_{t+1} can be expressed in terms of current and lagged innovations: $Y_{t+1}=A_0+\sum A_j Y_{t-j+1}+u_t$, where $Y_{t+1}=\{OIB_t^1, OIB_t^2, OIB_t^3, R_t^1, R_t^2, R_t^3\}$ represents net order imbalances and returns of the leading ADR, ETF, and CEF respectively. The lag length is chosen as k=6 by Akaike and Schwartz-Bayes criteria. Figure 2a-2f forecast the Order flow and Returns of OIBADR, OIBETF, OIBCEF, ReturnADR, ReturnETF, and ReturnCEF.

REFERENCE

[1] Admati, Anat and Paul C. Pfleiderer, 1988, A theory of intraday patterns: volume and price variability, Review of Financial Studies 1, 3-40.

[2] Bailey,W., G. Andrew Karolyi, and Carolina Salvac, 2006, The Economic Consequences of Increased Disclosure:Evidence from International Cross-listings, Journal of Financial Economics 81,175-213

[3] Bailey, W., Kee-Hong Bae, and Connie X. Mao, 2006, Stock Market Liberalization and the Information Environment, Journal of International Money and Finance 25, 404-428.

[4] Bailey, W., Kumar, A. and Ng, D., 2007, Foreign Investments of U.S. Individual Investors: Causes and Consequences, Working paper, Cornell University

[5] Bailey, W., Connie X. Mao, and Kulpatra Sirodom, 2006, Locals, Foreigners, and Multimarket Trading of Equities: Some Intraday Evidence, Working Paper, Cornell University

[6] Barber, Brad. M., and Terrance Odean, 2000, Trading is hazardous to your wealth: The common stock investment performance if individual investors, Journal of Finance 55, 773-806.

[7] Barber, Brad. M., and Terrance Odean, 2005, All the glitters: The effect of attention and news on the buying behavior of individual and institutional investors, Working paper, University of California, Davis.

[8] Bohn, H., Tesar, L., 1996. U.S. equity investment in foreign markets: portfolio rebalancing or return chasing? American Economic Review 86, 77-81.

[9] Brennan, M., Cao, H., 1996. Information, trade, and derivative securities. Review of Financial Studies 9 (1), 163-208.

[10] Brennan, M., 1998. Discussion: Has the rise of mutual funds increased market instability? Brookings-Wharton Papers on Financial Services, 263-267.

[11] Choe, Hyuk, Kho, Bong-Chan, and Rene M. Stulz, 1999, Do Foreign Investors Destabilize Stock Markets?: The Korean experience in 1997, Journal of Financial Economics 54, 227-264.

[12] Choe, Hyuk, Kho, Bong-Chan, and Rene M. Stulz, 2005, Do Domestic Investors Have an Edge? The Trading Experience of Foreign Investors in Korea, Review of Financial Studies 18, 795 - 830.

[13] Clark, J. Berko E., 1996, Foreign investment fluctuations and emerging market stock returns: the case of Mexico. Unpublished Working Paper. Federal Reserve Bank of New York.

[14] Craig, A, A. Dravid; and M. Richardson, 1995, Market E?ciency around the Clock: Some Supporting Evidence Using Foreign Based Derivatives, Journal of Financial Economics, 39, 161-180.

[15] Eun, C. S., and S. Shim, 1989, International Transmission of Stock Market Movements, Journal of Financial and Quantitative Analysis, 24, 241-256.

[16] Dahlquist. M.. and G. Robertsson, 2004, A Note on Foreigners' Trading and Price Effects across Firms, Joumal of Banking and Finance. 28, 615-632.

[17] De Long, J. Bradford, Andrei Shleifer Lawrence H. Summers, and Robert J.Waldmann, 1990a, Noise trader risk in financial markets, Journal of Political Economy 98, 703-738.

[18] De Long, J. Bradford, Andrei Shleifer Lawrence H. Summers, and Robert J.Waldmann, 1990b, Positive feedback investment strategies and destabilizing rational speculation, Journal of Finance 45, 379-395.

[19] Froot, K., O'Connell, P.G.J., Seasholes, M.S., 2001, The portfolio flows of international investors, Journal of Financial Economics, 59, 151-193.

[20] Froot, K. A., and T. Ramadorai, Institutional Portfolio Flows and International Investments, Review of Financial Studies, forthcoming

[21] Griffin, John M., Harris, Jeffrey H., and Selim Topaloglu, 2003, The Dynamics of Institutional and Individual Trading, Journal of Finance 58, 2285-.2320

[22] Griffin, John M., Federico Nardari, and R. M. Stulz, 2004, Daily cross-border equity flows: Pushed or pulled?, Review of Economics and Statistics, v86(3), 641-657.

[23] Grinblatt, Mark, and Matti Keloharju, 2000, The investment behavior and performance of various investor types: A study of Finland's unique data set, Journal of Financial Economics 55, 43-67.

[24] Harnao, Y; R.W.Masulis; and V. Ng, 1990, Correlations in Price Changes and Volatility across International Stock Markets, Review of Financial Studies, 3, 281-307.

[25] Hau, Harald, 2001a, Location matters: An examination of trading profits, Journal of Finance 56, 1951-1983.

[26] Hong, Harrison, and Jeremy C. Stein, 1999, A unified theory of underreaction, momentum trading, and overreaction in asset markets, Journal of Finance 54, 2143-2184

[27] Kaniel, Ron, Saar, Gideon and Sheridan Titman, 2006, Individual Investor Trading and Stock Returns, forthcoming in the Journal of Finance.

[28] Karolyi, A. and R. Stulz, 1996, Why Do Markets Move Together? An Investigation of US-Japan Stock Return Co-Movements, Journal of Finance, 51, 951-986.

[29] Karolyi. G. A., 2002, Did the Asian Financial Crisis Scare Foreign Investors Out of Japan?, Pacific Basin Finance Joumal. 10, 41 I -142.

[30] K. Ellis, R. Michaely, and M. O'Hara, 2000, The Accuracy of Trade Classification Rules: Evidence from Nasdaq, Journal of Financial and Quantitative Analysis, 35,(4), 529-551.

[31] Lakonishok, Josef, Andrei Shleifer, and Robert W. Vishny, 1992, The impact of institutional trading on stock prices, Journal of Financial Economics 32, 23-43.

[32] Lee, Charles M. C., and Mark Ready, 1991, Inferring trade direction from intraday data, Journal of Finance 46, 733-746.

[33] Richards, Anthony, 2005. Big fish in small ponds: The trading behavior of foreign investors in Asian emerging equity markets, Journal of Financial and Quantitative Analysis 40, 1-27.

[34] Seasholes, Mark S., 2000, Smart foreign traders in emerging markets, Working paper, University of California at Berkeley.

Chapter 4
Endogenous Information Acquisitions, Cost of Capital, and Comovement of Equity Returns

4.1 INTRODUCTION

The study of the comovement of asset returns has recently received great interests in finance literature. The cause of stock market covariation remains a puzzling issue. There are different theories that explain the comovement of the asset returns[28]. The traditional asset pricing theory shows that comovement in returns must be due to correlation in fundamental value. We call it fundamentals-based comovement. In behaviour literature, there exists an alternative theory which argues that return comovement is delinked from fundamentals due to market frictions or noise-trader sentiment. "Friction-based" and "sentiment-based" comovement come from three specific variables: the category, habitat, and information diffusion views (Barberis, Shleifer, and Wurgler (2005)). Empirical evidence cannot easily be explained by the fundamentals-based view of comovement so many scholars think it might be evidence of investor irrationality and fit with the friction-based or sentiment-based views. We want to revisit traditional asset pricing theory by introducing information market and try to give a good explanation for comovement of asset returns. We call it information-based comovement.

Trading based on private information and cost of information acquisitions could be potential causes of the comovement in stock returns if agents have superior knowledge about the common factors of the stock returns. On the other side, it is very common to explain why individuals trade assets in stock markets because

[28] Researchers have uncovered numerous patterns of comovement in asset returns. There are strong common factors in the returns of small-cap stocks, value stocks, closed-end funds, stocks in the same industry, and bonds of the same rating and maturity. There is common movement of individual stocks within national markets and also among international markets.

of their access to different information. To motivate differences in information, it is typically assumed that information is costly to acquire, so that some agents will buy information and some will not. But this explanation raises a lot of interesting questions: How much information will be acquired about stocks? How will this information be reflected in prices? How do informed and uninformed traders interact with one another? Does cost of the information acquisition affect the returns? Yet it is challenging to answer these questions. The reason is that in an equilibrium where information is costly to acquire, agents who choose not to purchase information nevertheless extract some information from the prices they observe, and so their demand will depend on the distribution of equlibrium prices. Information-based comovement has not been widely accepted because it is difficult to model information acquisitions and test the comovement based on data of investors' information.

To answer those questions, we introduce information market into the traditional asset pricing model and our model is based on the Grossman-Stiglitz rational expectations model (Grossman and Stiglitz (1980)) and employs specification of endogenous information acquisitions (Verrecchia (1982)). With endogenous costly information acquisitions, informed investors choose the level of precision of private information and pay cost of information acquisitions and make their trading decisions based on their information set. It will increase the price informativeness and have a better price quality if investor acquire more private signals and higher level of precision of private information. When the information is not costly, on average, the informed investors always trade more and gain higher expected returns than the uninformed with more private information. The most important results from this paper are the information structure and correlations of information costs do explain the comovement of the asset returns. A private information signal must have two features to produce comovement: First, its information set contains information not only about the value of the asset itself but also the value of many other assets; Second, it must be observed by many investors since the informed investors pay for acquiring it. The common source of information adds a new common shock to the assets, which causes apparent excess covariance in their returns. But if informed investors aggressively obtain abundant private informtion, it will decrease the comovement. In this sense, endogenous acquisitions of private information can be an important factor which affect the comovement of asset returns.

This paper also discusses about the information and cost of capital. O'hara and Easley(2004) investigate the role of information in affecting a firm's cost of capital with exogenous information acquisitions. In our model, with endogenous information acquisitions, it lowers required risk premium and reduces the cost of captial with more informed investors and more private information signals. Another important result we get is that it raises company's cost of capital with a greater precision of private information and higher information cost. O'hara and Easley(2004) show that greater precision of both private and public information directly lowers company's cost of capital because it will lower the riskiness of the asset to the uninformed. Firms could increase information disclosure to reduce cost of captial. Our result is just opposite to theirs. Costly information acquisitions will affect the cost of capital through two channels. First, a higher level of precision of private information, which pays a higher cost of information acquisitions, improves the price informativeness and it requires higher expected returns and raises the cost of capital. Second, informed investors pay for the private information and it can not be reflected in the trading price immediately. Uninformed investors can not easily infer the information from prices when private information is costly. The firm will disclose the information to the investors by the information market. Investors pay lower information cost for the high-demand information and pay higher information cost for the low-demand information. Firms could lower their cost of capital either by reducing the extent of private information or by increasing its dispersion across traders. On the other side, firms do not want to disclose the private information because of the moral hazard problems of self-reporting information or they want to make more profit by charging the information fees. Private information is not directly disclosed to the public and it raises the cost of capital.

The empirical literature on comovement has uncovered many facts that support a link between comovement and asymmetric information. Existing studies (See King, Sentana, and Wadhwani (1994), Karolyi and Stulz (1996) and Connolly and Wang (2003)) show that macroeconomic factors, such as macro news announcements and interest rate shocks, have a limited impact on international equity returns and are not responsible for the comovements. Albuquerque, Bauer and Schneider(2006) show that private information can explain the comovement of the asset returns across countries. Durnev, Morck, Yeung, and Zarowin(2003) show that having more institutional investors who acquire more information reduces comovement. Hameed, Morck and Yeung (2005) find that hiring more analysts are providing information that can produce comovement by using CRSP and IBES data (1984-2003). It verifies that information acquisition could be a good predictor for the comovement. Furthermore, firms with more analyst coverage have returns that predict more of the variation in other firms' returns, after controlling for covariance in fundamentals.

Our study is closely related with a growing literature which attempts to link the microstructure literature with asset pricing. Easley and O'hara(2004) developed a theoretical model to show why equilibium differences in asset returns will arise due to private information. Assets with greater private information and less public information will command a risk premium in equilibrium. This model provides a basis for analyzing the specific effects of private and public information on asset returns as well as for showing why factors such as microstructure would affect asset returns. Easley, Hvidkjaer and O'hara(2002) showed empirically that information-based trading and firm size are the predominant factors to explain the returns. Veldkamp (2006) introduces markets for information that generate high price covariance within a rational expectations framework allowing fixed information costs. Differently from Veldkamp (2006), we allow each individual investors purchase different private information signals and cost of information varies among the signals. We find that lower cost of information acquistions (i.e. higher informaiton disclosure) is associated with a lower cost of capital and information acqusition can generate comovement of stock returns. Our results mainly focus on the return comovement not price covariance.

Our work is also related with the numerous studies on the role of information asymmetry and information disclosure. Verrecchia (2001) have a detailed survey on disclosure. It shows the link between disclosure, efficiency and information asymmetry reduction. The greater disclosure lowers the component of the cost of capital that arises from information asymmetry. Diamond and Verrecchia (1991) suggests that greater voluntary disclosure should lower information asymmetry and reduce the cost of capital. Some other research (Kim and Verrecchia, 1994; McNichols and Trueman, 1994; Zhang, 2001) argues that increasing cost of capital effects may occur if the disclosures lead to a more asymmetric information environment than would exist in their absence. Cao (1999) show that the presence of derivative assets causes informed investors to acquire more precise information about asset returns. Holden and Subrahmanyam (2002) show that the dynamic behavior of asset price movements prior to significant news events, such as eamings announcements, could be explained by the model[29] with the introduction of sequential endogenous information acquisition. Bailey and Karolyi(2006) show that the changes in the firms' disclosure environment affect return volatility and trading volume.

This paper is organized as follows. Section 2 develops a rational expectations model with endogenous information acquisitions. We characterize the demand of the informed and uninformed traders, and we demonstrate that a nonrevealing rational expectations equilibrium exists. In Section 3, we derive the optimal cost of information acquisitions and analyze the specific influence on private and public information and informaiton acquistions on individual trading behaviour and asset returns. Section 4 explain the comovement of the stock returns with endogenous information acquisitions. Section 5 explore the properties of the information market and effect on the cost of capital. Section 6 concludes.

4.2 THE MODEL

Our model is based on the Grossman-Stiglitz rational expectations model (Grossman and Stiglitz (1980)) and employs specification of endogenous information acquisitions (Verrecchia (1982)). We want to explore the effect on the cost of capital and expected returns with endogenous information acquisitions.

[29] The model embeds information asymmetry into the work of Epstein and Tumbull (1980).

4.2.1 Basic Structure

We consider a multiasset rational expectation model. There is a continuum of investors, indexed by $i \in [0,1]$. investors live for T periods, time $t = 0,\ 1, \cdots, T-1, T$. We assume there is one risk-free asset bond(money) which has a constant price of 1. There are M risky assets[30] indexed by $m = 1, 2, ..., M$. Trading is allowed to take place in T trading sessions which are held at times $t = 0, 1, \cdots, T-1$. The asset payoffs are realized and consumption takes place at time T after the last trading session. At time 0, each investor endows with $\overline{m}_0$ units of money. There is no intermediate consumption in the model.

During the trading periods, end-of-period value of the asset is given by $v^i_{mt} \sim N(\overline{v}_m, \rho^{-1}_m)$. The per capita supply of the asset m is $x^i_{mt} \sim N(\overline{x}_m, \eta^{-1}_m)$ for investor i. We denote x_{mt} as the aggregate supply of the asset m at time t. Asset supplies are independent across periods and all other random variables. Asset prices p_{mt} are determined in the market. Investor i trades at time $t = 0, \cdots T-1$ at prices $P^t = (p_{1t}, p_{2t}, ..., p_{Mt})$ per share and receives payoffs of $v^i = (v^i_1, ..., v^i_M)$ per share at $t = T$. v^i_m is followed by normal distribution, i.e. $v^i_m \sim N(\overline{v}_m, \rho^{-1}_m)$.

At the beginning of period 0, information market is open. There are two types of information signals about the future values of these assets, private and public. Public signals are accessible to all investors. Yet private signals are not costless. Investor i need to decide whether he wants to acquire private information. After investors make a decision, the nature knows the fraction of informed investors μ_{mt} which is determined by the model. If investor i gets private information, he need to pay the corresponding cost. For simplicity, we assume total number of information

[30] If we want to explain the international asset market and show the behaviour of the asset returns, we could define the risky assets as follows without loss of generaliztion. When $m = 1$, it is treated as a domestic asset. When $m = 2, 3, ..., M$, the market portfolio of each country is treated as a single risky asset, and currency risk is ignored.

signals about the future value of asset m are I_m[31]. All the signals are asset-specific.

If investor i chooses to acquire private information and become informed, we assume the fraction of private information signal for investor i is α_m[32]. Trader i receives private signals $S^i_{mt} = [s^i_{m_1 t}, s^i_{m_2 t} \cdots, s^i_{m_{\alpha_m I_m} t}]'$, where S^i_{mt} follows jointly normal distribution with mean $\overline{V}$ and precision matrix Γ, i.e. $S^i_{mt} \sim N(\overline{V}, \Gamma)$ and $s^i_{m_j t}$ is normally distributed with mean $\overline{v}_m$ and precision γ_m, $j = 1, 2, ..., \alpha_m I_m$. Investor i's cost function of acquiring private information at time t is defined as $c^i_{mt} = C^m(\gamma_m)$. Information cost c^i_{mt} is related with the precision of the private information γ_m. $C^m(.)$ is strictly increasing, convex and twice continuously differentiable. For simplicity, we just assume informed investors pay the same cost of acquiring private information for the same asset. Yet we assume the effort of acquiring private informtion about different assets are different, i.e. $c^i_{mt} = C^m(.) \neq c^i_{nt} = C^n(.)$, even if they have the same precision of private information($\gamma_m = \gamma_n$), the cost of information acquistions might still be different.

If the information cost is not acceptable by the investor i, he could choose to be an uninformed investor and only receive public information signals. All traders observe the public information. Define public signals received by trader i as $Y^i_{mt} = [y^i_{m_1 t}, y^i_{m_2 t} \cdots, y^i_{m_{(1-\alpha_i) I_i} t}]'$, where Y^i_{mt} follows jointly normal distribution with mean $\overline{V}$ and precision matrix N, i.e. $Y^i_{mt} \sim N(\overline{V}, N)$ and y^i_{mst} is normally distributed with mean $\overline{v}_m$ and precision N_m, $s = 1, 2, \cdots, (1 - \alpha_m) I_m$. For simplicity, we assume that $\Gamma_{mm} = 0, N_{mm} = 0$.

At time t, all investors know the distributions of all random variables.

[31] In order to compare the result with EASLEY and O'HARA(2004), we make this assumption.

[32] For each asset m, investor might receive different amount of private signals instead of exactly $\alpha_m I_m$. For simplicity, we just assume investor i receives the same amount of signals for each asset.

4.2.2 Equilibrium

The investor i only cares about his wealth W_t^i at the end of time t and has CARA untility functions with coefficient of risk aversion $\delta > 0$. The investor i have an endowment of money $\overline{m}^i$ at time 0. Each investor chooses his demand for assets $m = 1, 2, \cdots, M$ to maximize his expected untility subject to his budget constraint at time t, $t = 0, 1, \cdots, T-1$. We denote trader $i's$ demand for the assets by $D_t^i = (Z_{1t}^i, Z_{2t}^i, \cdots, Z_{Mt}^i)'$ and for the bond by $B_t^i = m_t^i$. Trader i's wealth at time t is $W_t^i = B_t^i + v_t^i D_t^i$.

At time t, informed and uninformed investors observe different information signals about the assets, so they have different beliefs. Informed investor i observe both private information signals S_{mt}^i and public information signals Y_{mt}^i. By Bayes' rule, an informed investor i uses $\{S_{mt}^i, Y_{mt}^i\}$ to update his beliefs. $v_{mt}^i \mid \{S_{mt}^i, Y_{mt}^i\}$ is normally distributed with mean $\overline{v}_m^i$ and precision ρ_m^i. Denote a vector by $1 = (1, 1, \cdots, 1)$.

$$\begin{aligned} v_{mt}^i \quad &\mid \quad \{S_{mt}^i, Y_{mt}^i\} \sim N(\overline{v}_m^i, \rho_m^{i-1}) \\ \overline{v}_m^i \quad &= \quad \frac{\rho_m \overline{v}_m + \gamma_m 1 S_{mt}^i + \gamma_m 1 Y_{mt}^i}{\rho_m + \gamma_m I_m} \\ \rho_m^i \quad &= \quad \rho_m + \gamma_m I_m \end{aligned} \tag{4.2.1}$$

Informed investor i's demand for the asset m at time t is given by

$$\begin{aligned} z_{mt,I}^i &= \frac{E(v_{mt}^i \mid \{S_{mt}^i, Y_{mt}^i\}) - p_{mt} - c_{mt}^i}{\delta Var(v_{mt}^i \mid \{S_{mt}^i, Y_{mt}^i\})} \\ &= \frac{\rho_m \overline{v}_m + \gamma_m 1 S_{mt}^i + \gamma_m 1 Y_{mt}^i - (p_{mt} + C^m(\gamma_m))(\rho_m + \gamma_m I_m)}{\delta} \end{aligned} \tag{4.2.2}$$

We denote informed investor i's demand for the assets as

$$D_{t,I}^i = (z_{1t,I}^i, z_{2t,I}^i, \cdots, z_{Mt,I}^i)'.$$

Uninformed investors can only observe the public information signals Y_{mt}^i. But they know the distribution of private information signals and they rationally infer how it affects the demands of the informed investors and the equilibrium prices. To learn from the price, uninformed investors must conjecture a form for the price function and in a rational expectation equilbrium the conjecture must be correct. Suppose the uninformed conjecture the price function

$$p_{mt} = a_t\overline{v}_m + b_t 1 S_{mt}^i + c_t 1 Y_{mt}^i - d_t x_{mt} + e_t \overline{x}_m - g_t X_{m,t-1} - f_t C^m(\gamma_m)$$

where $a_t, b_t, c_t, d_t, e_t, f_t$ and g_t are coefficients to be determined and $X_{m,t-1}$ is the aggregate supply of the assets until time $t-1$. i.e. $X_{m,t-1} = \sum_{j=0}^{t-1} x_{mj}$.

For convenience the observed random variable[33]

$$\begin{aligned} \theta_{mt}^i &= \frac{p_{mt} - a_t\overline{v}_m - c_t 1 Y_{mt}^i + \overline{x}_m(d_t - e_t) + g_t X_{m,t-1}}{b_t \alpha_m I_m} \\ &= \frac{1 S_{mt}^i}{\alpha_m I_m} - \frac{d_t}{b_t \alpha_m I_m}(x_{mt} - \overline{x}_m) - \frac{f_t C^m(\gamma_m)}{b_t \alpha_m I_m} \end{aligned} \tag{4.2.3}$$

Calculation shows that θ_{mt}^i is normally distributed with mean $\overline{\theta}_m$ and precision ρ_{θ_m}.

$$\begin{aligned} \theta_{mt}^i &\sim N(\overline{\theta}_m, \rho_{\theta_m}^{-1}) \\ E\theta_{mt}^i &= \overline{\theta}_m = \overline{v}_m - (\frac{f_t}{b_t \alpha_m I_m})\overline{c}_m \\ \rho_{\theta_m} &= (\frac{1}{\alpha_m I_m}\gamma_m^{-1} + (\frac{d_t}{b_t \alpha_m I_m})^2 \eta_m^{-1})^{-1} \end{aligned} \tag{4.2.4}$$

So uninformed investors uses $\{Y_{mt}^i, \theta_{mt}^i\}$ to update his beliefs. By Bayes' rule, $v_{mt}^i \mid \{Y_{mt}^i, \theta_{mt}^i\}$ is normally distributed with mean $\overline{v}_m^i$ and precision ρ_m^i.

$$\begin{aligned} v_{mt}^i &\mid \{Y_{mt}^i, \theta_{mt}^i\} \sim N(\overline{v}_m^i, \rho_m^{i-1}) \\ \overline{v}_m^i &= \frac{\rho_m \overline{v}_m + \gamma_m 1 Y_{mt}^i + \rho_{\theta_m}\theta_{mt}^i}{\rho_m + \gamma_m(1-\alpha_m)I_m + \rho_{\theta_m}} \\ \rho_m^i &= \rho_m + \gamma_m(1-\alpha_m)I_m + \rho_{\theta_m} \end{aligned} \tag{4.2.5}$$

[33]See Easley and O'hara(2003) for this price function conjecture.

Uninformed investor i's demand for the asset m at time 1 is given by

$$\begin{aligned} z^i_{mt,U} &= \frac{E(v^i_{mt} \mid \{Y^i_{mt}, \theta^i_{mt}\}) - p_{mt}}{\delta Var(v^i_{mt} \mid \{Y^i_{mt}, \theta^i_{mt}\})} \qquad (4.2.6) \\ &= \frac{\rho_m \overline{v}_m + \gamma_m 1 Y^i_{mt} + \rho_{\theta_m} \theta^i_{mt} - p_{mt}(\rho_m + \gamma_m(1-\alpha_m)I_m + \rho_{\theta_m})}{\delta} \end{aligned}$$

We denote uninformed investor i's demand for the assets as

$$D^i_{t,U} = (z^i_{1t,U}, z^i_{2t,U}, \cdots, z^i_{Mt,U})'.$$

In the equilibrium, the asset market for each asset m clears, i.e.

$$\mu_{mt} z^i_{mt,I} + (1-\mu_{mt}) z^i_{mt,U} = X_{m,t} \qquad (4.2.7)$$

We find the rational expectation equilibrium by solving equation (4.2.7) for p_{mt} and then verifying that p_{mt} is of the form conjectured in (3). Proposition 1 charateriizes the equilibrium.

Proposition 1 *There exists a partially revealing equilibrium at time t in which*

$$p^*_{mt} = a_t \overline{v}_m + b_t 1 S^i_{mt} + c_t 1 Y^i_{mt} - d_t x_{mt} + e_t \overline{x}_m - g_t X_{m,t-1} - f_t C^m(\gamma_m) \qquad (4.2.8)$$

where

$$\begin{aligned} a_t &= \frac{\rho_m}{M}, b_t = \frac{\mu_{mt}\gamma_m}{M}(1 + \frac{A\rho_m}{\rho_{\theta_m}}), c_t = \frac{\gamma_m}{M} \\ d_t &= \frac{(A+1)\delta}{M}, e_t = \frac{A\delta}{M}, g_t = \frac{\delta}{M} \\ f_t &= \frac{(1+A)BC}{M} = \frac{(1+A)B}{(B-1+(A+1)\mu_{mt})} \\ M &= (\frac{B-1}{\mu_{mt}} + A + 1)C, C = \alpha_m I_m \mu_{mt} \gamma_m \\ A &= \frac{(1-\mu_{mt})\rho_{\theta_m}}{\alpha_m I_m \mu_{mt} \gamma_m}, B = \frac{\mu_{mt}(\rho_m + \gamma_m I_m)}{\alpha_m I_m \mu_{mt} \gamma_m} \\ \rho_{\theta_m} &= [\frac{1}{\alpha_m I_m}\gamma_m^{-1} + (\frac{\delta}{\alpha_m I_m \mu_{mt} \gamma_m})^2 \eta_m^{-1}]^{-1} \end{aligned}$$

Proof. See Appendix. ■

The proposition 1 demonstrates that there exists a rational expectation equilibrium in which prices are partially revealing. Easley and O'hara(2004) derives the REE price when there is no endogenous information acquistions. When we introduce endogenous information acquisitions, the informed investors expect higher equity returns. Since the uninformed investors can infer some information from the price, there should be a threshold under which the investors is willing to be informed. The partial revealing equilibrium price is affected by the value of the asset, private and public signals, per capita of supply, aggregate supply of the asset and cost of information acquisitions. Informed investors want to reduce risk and acquire higher risk premium by paying information cost.

Proposition 2 *The expected return on stock m is given by*

$$E(v_{mt} - p_{mt}) = \frac{(t+1)\delta\overline{x}_m + BC(1+A)C^m(\gamma_m)}{M} \tag{4.2.9}$$

where A, B, C, M is given in Proposition 1.

Proof. See Appendix. ■

The expected return depends on the information structure since the levels of public and private information influence the equlibrium return demanded by different investors. Proposition 2 shows the expected return per share to hold asset m for both informed investors and uninformed investors. The expected return reveals that the risk premium of a stock depends on risk preferences δ, the mean of stock supply per capita $\overline{x}_m$,time t, information structure and cost of information acquistions $C^m(\gamma_m)$. O'hara and Easley(2004) has talked about the risk premium when there are no information acquisitions for the investors in the market. The risk premium is highly depending on the risk preference δ and average stock supply per capita $\overline{x}_m$. If the investors are risk neutral or average stock supply per capita $\overline{x}_m$ is equal to zero, then the underlying risk is not important to them at all and there is no risk premium for any stock. But if we allow endogenous information acquisitions, the expected return is higher. The asset's underlying risk is higher and it needs to have higher information acquisitions to offset the risk.

The risk premium is also affected by time t and information structure. The longer the trading period is, the more information the investors get, the higher the risk premium is. The uninformed investors can infer some information from the price and the supply of the stock. As a signal θ^i_{mt}, the precision of signal θ^i_{mt} depends on the precision of the private signals γ_m and the stock supply η_m. Holding other conditions constant, the greater the uncertainty about the private information γ_m, the higher cost the investors pays, the greater the uncertainty about the θ^i_{mt} from which you can infer information.

4.3 ENDOGENOUS INFORMATION ACQUISITIONS AND INVESTOR BEHAVIORS

In this section, we investigate the investor behaviors and expected equity returns when endogenous information acquisitions are introduced. The natural questions we are interested in are: How is the optimal cost of information acquisitions determined? How does the precision of private information affect investors' decisions? Do informaiton acquistions affect the expected asset returns and asset holdings? We try to answer those questions in our rational expectation model. Both Informed and uninformed investors maximizes their expected utilities according to their constraints. Define U^i_{tI} and U^i_{tU} are indirect utility function of investor i if he chooses to be informed and uninformed respectively, i.e. $U^i_{tI} = E(-e^{-\gamma W^i_{tI}} \mid \{S^i_{mt}, Y^i_{mt}\})$. μ_{mt} is the fraction of informed investors. Social planner maximizes the welfare of all the investors. i.e.

$$\underset{\mu_{mt},\gamma_m}{Max}\,\mu_{mt}U^i_{tI}+(1-\mu_{mt})U^i_{tU} \tag{4.3.1}$$

Proposition 3 *In a rational expectation model, there exist an optimal level of precision of private information γ^*_m, optimal cost of information acquisitions C^*_m and the equilibrium fraction of informed investors μ^*_m for asset m where social optimality approaches.*

$$\gamma^*_m = Max\{0,\gamma^*_m \left| \exp\left(\frac{-C^m(\gamma_m)^2+2C^m(\gamma_m)(LE(p_{mt}))}{2(\rho_m+\gamma_m(1-\alpha_m)I_m+\rho_{\theta_m})^{-1}\delta^{2-1}}\right)=1\right.\}$$

Proof. See Appendix. ■

By proposition 2, since we introduce endogenous information acquisitions into our rational expectation model, in the equilibrium the marginal value of private information should be equal to the marginal cost of private information. Therefore informed investor will choose optimal precision level of asset m, i.e. γ^*_m. The most critical result here is that we can endogenously derive the equilibrium fraction of informed investors. That means investors in the market could make their investment decisions based on their own information set. In this setup, it is more informative to study the behaviour and investment decisions of all investors.

Proposition 4 *In the information market, informed investors' cost of information acquisitions has an upper bound C^*. If the precision level of private information is not more than γ^*_m, investor will choose to be informed; otherwise, he will stay uninformed.*

Proof. See Appendix. ■

If investor pays the cost of acquiring private information, his expected indirect utility should be at least larger than those uninformed. Otherwise he stays uninformed and doesn't need to pay extra money to acquire more information. So there should have a threhold of the cost of information acquisitions and the private information can not be so costly that the investors even could not better off after getting more information.

With endogenous information acquisitions, informed investors do not simply acquire the same amount of private information across different assets. First, if the informed investor acquires more private signals(that is, the fraction of private information signals α_m increases), he will get more information about the payoff of the asset and his investment decision based on his information set will be more profitable and accurate. Second, if informed investors acquire a higher level of precision of private information from one asset, intuitively price informativeness increases. Meanwhile it reduces the price change volatility and have a better price quality. Follow Verrecchia (1982) and cao(1999), we use the conditional variance of the underlying value given the equilibrium price, $Var(v \mid p)$, as a measure for the level of informativeness of price. Define the price change volatility $Var(v - p)$ to measure the quality of the price. We summarize the results in proposition 5.

Proposition 5 *(i) Informed investor has a higher level of informativeness and reduces the price change volatility if he acquires more private information. (ii) Informed investor investor has a higher level of informativeness and reduces the price change volatility if he acquires a higher level of precision of private information.*

Proof. See Appendix. ■

We want to explore whether the information acquisitions affect the expected asset returns and asset holdings.

Proposition 6 *When the information is not too costly, on average, the informed investors will hold more of risky assets than uninformed investors when the private* *information signals good news; On the contrary, informed investors will short more of risky assets when the private information signals bad news.*

Proof. See Appendix. ■

With endogenous information acquisitions, informed investors pay for the acquisitions of private information. They attain more valuable information than uninformed investors. So the informed investors hold more of the assets when the private information signals good news. Otherwise they short more if the private signals are bad news. The uninformed investors only obtain public information signals so the public information signals have a greater effect on the uninformed's belief than the informed's belief. If the public information signals are relatively delivering the correct information about the payoff of the asset, this induces the uninformed to trade relatively more of the asset which closes the gap between the informed and uninformed holdings. If the public information signals don't reveal the correct information as the private information signals do, the uninformed investors might make wrong decisions or trade less than informed investors.

Proposition 7 *The informed investors receive higher expected returns than the uninformed investors for each period.*

Proof. See Appedix. ■

Proposition 7 shows the expected returns of informed investors is higher than the uninformed investors because both the higher quality of information and the higher risk of portfolio increase informed investors' expected asset return. Informed investors pay cost of information acquisitions to acquire more private information about the payoff of the assets. The higher quality information makes the informed have a better investment decisions than the uninformed so they expect higher returns. This occurs because uninformed investors can not perfectly infer the information from prices and bear more risks when there exists private information. The endogenous information acquistions do affect the expected returns.

4.4 ENDOGENOUS INFORMATION ACQUISITIONS AND COMOVEMENT OF ASSET RETURNS

There are different theories which explain the comovement of the asset returns. The traditional asset pricing theory show that comovement in returns to correlation in news about fundamental value. We call it fundamentals-based comovement. The alternative theory argues that return comovement is delinked from fundamentals due to market frictions or noise-trader sentiment. A second broad class of "friction-based" and "sentiment-based" comovement comes from three specific variables: the category, habitat, and information diffusion views (Barberis, Shleifer and Wurgler (2005)). Empirical evidence cannot easily be explained by the fundamentals-based view of comovement, but fit with the friction-based or sentiment-based views. In this paper, we introduce information market into the traditional asset pricing model and try to investigate whether it will affect the pattern of asset returns with endogenous information acquisitions.

Proposition 8 *For asset m, n, the expected returns of asset m and n comove together and comovement is related to the information structure and covariance of information costs.*

Proof. See Appendix. ■

For simplicity, we have assumed that the payoffs of the assets are not related to each other. What we want to find is whether any other factors affect the co-movement of the stock returns. Investors pay the information acquisition cost and acquire more private information. Intuitively, information acquisition is related with the precision of private information. The higher the precision of private information is, the more they know about the risky asset, the lower the information cost is. Information about the value of one risky asset also reveals some information about the value of another risky asset. A private information signal must have two features to produce comovement: First, its information set contains information not only about the value of the asset itself but also the value of many other assets; Second, it must be observed by many investors since the informed investors pay for acquiring it. The common source of information adds a new common shock to the assets, which causes apparent excess covariance in their returns.

If the investors obtain the information set about the two assets via information acquisitions which are correlated, then the expected returns of the two risky assets comove together. In this sense, acquisitions of private information can be an important factor which affect the comovement of international stocks. Will investors coordinate on receiving private information that can cause asset returns to comove? Public information signals could not generate comovement because all the investors could observe public information which might not be a good prediction of the asset values. In an information market, suppliers must provide the highest-value private signals to be competitive. Since private information signals that predict many assets' values generate more expected profit for investors, market forces induce suppliers to sell private information signals to investors at different prices. Correlation between the cost of getting private information signals will cause the comovement of the asset returns.

Some empirical work has supported what we get in the paper. Hameed, Morck and Yeung (2005) find that hiring more analysts are providing information that can produce comovement by using CRSP and IBES data (1984-2003). It verifies the proposition 8 that information acquisition could be a good predictor for the comovement. Furthermore, firms with more analyst coverage have returns that predict more of the variation in other firms' returns, after controlling for covariance in fundamentals. This result suggests investors are doing what agents in the model do: They acquire more information about one firm's return to better predict another firm's return. The information ends up being incorporated into both returns and makes one a more accurate predictor of the other. Albuquerque, Bauer and Schneider(2006) show that private information can explain the comovement of the asset returns across countries.

Proposition 9 *In rational expectations equilibrium, more informed investors increase comovement of the returns in each period.*

Proof. See Appendix. ■

Since we allow investors purchase different private information signals at different cost in the information market, some investors have different information set and some might have a better prediction of stock value. The observing private information signals will affect informed investors' portforlio holdings. More people becoming informed about one asset increases excess covariance. The more people making these inferences, the more returns comove.

Proposition 10 *If informed investors acquire more private information, it increases the comovement of asset returns. But if informed investors aggressively obtain abundant private informtion, it will decrease the comovement.*

Proof. See Appendix. ■

When informed investors acquire more private informaiton, the asset prices reveal more information. Investors make stronger inferences about the assets and it will increase the comovement of the asset returns. Public information signals could not generate comovement because all the investors could observe public information which might not be a good prediction of the asset values. When some investors are informed, the price of the asset is more informative. It lowers the risk for the uninformed because information has effect on the asset's equilibrium price. However, if informed investors aggressively acquire more private information and information becomes more abundant, it will not increase but decrease the comovement. If information demand starts spilling over into other assets, comovement falls. As more private signals are obtained by informed investors, the assets will be priced based on less common information and more on other factors and it will reduce the comovement. In short, comovement arises because the existing asymmetric information. When information becomes more complete, the effect disappears. Durnev, Morck, Yeung, and Zarowin(2003) show that having more institutional investors who acquire more information reduces comovement. This finding confirms proposition 10, that the comovement effect decreases when much more signals are observed.

4.5 INFORMATION MARKETS AND COST OF CAPITAL

O'hara and Easley(2004) investigate the role of information in affecting a firm's cost of capital. They show that differences in the composition of information between public and private information do affect the cost of capital with investors demanding a higher return to hold stocks with greater private information. In their model, the information acquisition is exogenous. In our model, we introduce endogenous information acquisitions in a rational expectations model. The question is how the private information affects the cost of capital with costly information acquisitions. To address the question, we use the same definition of the cost of capital as in O'hara and Easley(2004). The cost of capital to a firm issuing the stock is measured by the equilibrium required return. We define the cost of capital as $CC_{mt} = E(v_{mt} - p_{mt})$.

Proposition 11 *(i) Informed investor has a higher equilibrium required return and raises the cost of capital if he acquires more private information signals. (ii) The greater fraction of informed investors reduces the cost of capital.*

Proof. See Appedix. ■

Informed investors pay information cost to acquire more private information signals, so it will have a higher expected required returns. So acquiring higher private information raises the cost of capital. A firm whose stock has relatively more private information and less public information thus faces a higher cost of equity capital.

Proposition 8 (ii) shows with endogenous information acquisition more informed investors lowers required risk premium and reduces the cost of captial. It is consistent with the result of O'hara and Easley(2004). When private information is costly, the cost of private information is determined by the demand in the information market. More investors acquire private information of one asset and it increases the demand for the information for that asset. Firms charge more for low-demand information than for high-demand information. The low price of high-demand information makes investors want to purchase the same information that others are purchasing. More investors know the private information and the stock is less risky for informed investors than uninformed investors. On average, more investors are informed, the infomation will be revealed to the uninformed with a greater precision. It lowers the required risk premium and reduces the cost of capital.

Proposition 12 *Informed investor has a higher equilibrium required return and raises the cost of capital if he acquires a higher level of precision of private information and pays a higher cost of informtion acquisitions.*

Proof. See Appedix. ■

O'hara and Easley(2004) show that greater precision of both private and public information directly lowers company's cost of capital because it will lower the riskiness of the asset to the uninformed. Firms could increase information disclosure to reduce cost of captial. Our result is just opposite to theirs. With costly information acquisitions, it will affect on the cost of capital through two channels. First, the private information is not freely accessible to the public. When informed investor acquires a higher level of precision of private information and pays a higher cost of informtion acquisitions, they obtain better quality of private information than the uninformed because we assume the private information is more informative. That means informed investors receive higher expected return which raises the cost of capital otherwise they will choose to be uninformed. Second, informed investors pay for the private information and it can not be reflected in the trading price immediately. Uninformed investors can not easily infer the information from prices when private information is costly. They think the stock is riskier. The firm will disclose the information to the investors by the information market. Investors pay lower information cost for the high-demand information and pay higher information cost for the low-demand information. Firms could lower their cost of capital either by reducing the extent of private information or by increasing its dispersion across traders. On the other side, firms do not want to disclose the private information because of the moral hazard problems of self-reporting information or they want to make more profit by charging the information fees. Private information is not directly disclosed to the public and it raises the cost of capital. Higher cost of information acquisitions imply the lower information disclosure. This can be accomplished by a firm's selection of its accounting standards, and through its corporate disclosure policies. The extent that analysts provide credible information about the company can affect the information disclosure. Lower cost of information acquistions (i.e. Having more active analysts for a company) can reduce a company's cost of capital. Bhattacharya and Daouk(2002) show that the enforcement of incider trading law is associated with a lower cost of capital. Existing the Incider Trading Law makes incider trading costly to get private information. In this sense, higer cost of information acquisitions is associated with higher cost of capital.

4.6 CONCLUSION

This paper presents a rational expectations model with endogenous costly information acquisition to examine the role of information, asset returns and investor behaviour. Informed investors can choose what level of precision of private information and pay cost of information acquisitions and make their trading decisions based on their information set. Acquiring more private signals and higher level of precision of private information will increase the price informativeness and have a better price quality. On average, the informed investors always trade more and gain higher expected returns than the uninformed.

The information structure and correlations of information costs do explain the comovement of the asset returns. If informed investors acquire more private information or more investors are informed, it increases the comovement of asset returns. But if informed investors aggressively obtain abundant private informtion, it will decrease the comovement.

Endogenous information acquisitions could affect the firm's cost of capital. It lowers required risk premium and reduces the cost of captial with more informed investors and more private information signals. Another important result we get is that it raises company's cost of capital with a greater precision of private information and higher information cost. Lower cost of information acquistions (i.e. Having more active analysts for a company) can reduce a company's cost of capital.

APPENDIX

Proof of Proposition 1.

It is sufficient to show that there is an equilibrium price of the form given in the proposition. From (2) to (8), we solve for p_{mt} and get the following

$$\begin{aligned} & \mu_{mt}\frac{\rho_m\overline{v}_m+\gamma_m 1S^i_{mt}+\gamma_m 1Y^i_{mt}-(p_{mt}+C^m(\gamma_m))(\rho_m+\gamma_m I_m)}{\delta}+ \\ & (1-\mu_{mt})\frac{\rho_m\overline{v}_m+\gamma_m 1Y^i_{mt}+\rho_{\theta_m}\theta^i_{mt}-p_{mt}(\rho_m+\gamma_m(1-\alpha_m)I_m+\rho_{\theta_m})}{\delta} \\ = \; & X_{m,t} \end{aligned} \tag{A1}$$

Then we need to substitute (4) to (A1) and we can get

$$\frac{d_t}{b_t}=\frac{\delta}{\mu_{mt}\gamma_m},\frac{f_t}{b_t}=\frac{(\rho_m+\gamma_m I_m)}{\gamma_m} \tag{A2}$$

And by (5) and (A2),

$$\begin{aligned} \rho_{\theta_m} &= \left(\frac{1}{\alpha_m I_m}\gamma_m^{-1}+\left(\frac{\delta}{\mu_{mt}\gamma_m\alpha_m I_m}\right)^2\eta_m^{-1}\right)^{-1} \\ E\theta^i_{mt} &= \overline{\theta}_m=\overline{v}_m-\left(\frac{\rho_m+\gamma_m I_m}{\gamma_m\alpha_m I_m}\right)\overline{c}_m \\ \theta^i_{mt} &= \frac{1S^i_{mt}}{\alpha_m I_m}-\frac{\delta}{\mu_{mt}\gamma_m\alpha_m I_m}(x_{mt}-\overline{x}_m)-\frac{(\rho_m+\gamma_m I_m)C^m(\gamma_m)}{\gamma_m\alpha_m I_m} \end{aligned} \tag{A3}$$

Then we get

$$\begin{aligned} p^*_{mt} = \; & [\rho_m\overline{v}_m+(\mu_{mt}\gamma_m+\frac{(1-\mu_{mt})\rho_m}{\alpha_m I_m})1S^i_{mt}+\gamma_m 1Y^i_{mt} \\ & -(\frac{(1-\mu_{mt})\rho_{\theta_m}\delta}{\alpha_m I_m\mu_{mt}\gamma_m}+\delta)x_{mt}+\frac{(1-\mu_{mt})\rho_{\theta_m}\delta}{\alpha_m I_m\mu_{mt}\gamma_m}\overline{x}_m-\delta X_{m,t-1} \\ & -(\mu_{mt}(\rho_m+\gamma_m I_m)+\frac{(1-\mu_{mt})\rho_{\theta_m}(\rho_m+\gamma_m I_m)}{\alpha_m I_m\gamma_m})C^m(\gamma_m)]/ \\ & (\rho_m+(1-\alpha_m+\alpha_m\mu_{mt})\gamma_m I_m+(1-\mu_{mt})\rho_{\theta_m}) \end{aligned} \tag{A4}$$

where

$$\begin{aligned} a_t &= \frac{\rho_m}{M}, b_t=\frac{\mu_{mt}\gamma_m}{M}+\frac{(1-\mu_{mt})\rho_m}{M\alpha_m I_m}, c_t=\frac{\gamma_m}{M} \\ d_t &= \frac{(1-\mu_{mt})\rho_{\theta_m}\delta}{M\alpha_m I_m\mu_{mt}\gamma_m}+\frac{\delta}{M}, e_t=\frac{(1-\mu_{mt})\rho_{\theta_m}\delta}{M\alpha_m I_m\mu_{mt}\gamma_m} \\ g_t &= \frac{\delta}{M}, f_t=\frac{\mu_{mt}(\rho_m+\gamma_m I_m)}{M}+\frac{(1-\mu_{mt})\rho_{\theta_m}(\rho_m+\gamma_m I_m)}{M\alpha_m I_m\gamma_m} \\ M &= \rho_m+(1-\alpha_m+\alpha_m\mu_{mt})\gamma_m I_m+(1-\mu_{mt})\rho_{\theta_m} \\ \rho_{\theta_m} &= [\frac{1}{\alpha_m I_m}\gamma_m^{-1}+(\frac{\delta}{\alpha_m I_m\mu_{mt}\gamma_m})^2\eta_m^{-1}]^{-1} \end{aligned}$$

The equation (A4) is of the conjectured form (9) so it is a rational expectation equilibrium.

■

Proof of Propositon 2.

By proposition 1, the expected return on stock m is

$$\begin{aligned} E(v_{mt} - p_{mt}) &= E(v_{mt} - (a_t \overline{v}_m + b_t 1 S^i_{mt} + c_t 1 Y^i_{mt} - d_t x_{mt} \\ &\quad + e_t \overline{x}_m + g_t X_{m,t-1} - f_t c^i_{mt})) \\ &= \overline{v}_m(1 - a_t - b_t \alpha_m I_m - c_t(1-\alpha_m) I_m) + \overline{x}_m(d_t + t g_t - e_t) + f_t \overline{c}_m \end{aligned} \tag{A5}$$

$$E(p_{mt}) = \overline{v}_m - \frac{(t+1)\delta}{M}\overline{x}_m - (\frac{\mu_{mt}(\rho_m + \gamma_m I_m)}{M} + \frac{(1-\mu_{mt})\rho_{\theta_m}(\rho_m + \gamma_m I_m)}{M \alpha_m I_m \gamma_m})\overline{c}_m$$

Using the coefficients from Proposition 1, computation shows that

$$\begin{aligned} 0 &= 1 - a_t - b_t \alpha_m I_m - c_t(1-\alpha_m) I_m \\ d_t + t g_t - e_t &= \frac{(t+1)\delta}{M} \\ f_t &= \frac{\mu_{mt}(\rho_m + \gamma_m I_m)}{M} + \frac{(1-\mu_{mt})\rho_{\theta_m}(\rho_m + \gamma_m I_m)}{M \alpha_m I_m \gamma_m} \end{aligned}$$

Thus, we have

$$\begin{aligned} E(v_{mt} - p_{mt}) &= \frac{(t+1)\delta \overline{x}_m + \frac{(\alpha_m I_m \mu_{mt} \gamma_m + (1-\mu_{mt})\rho_{\theta_m})(\rho_m + \gamma_m I_m)}{\alpha_m I_m \gamma_m}\overline{c}_m}{\rho_m + (1 - \alpha_m + \alpha_m \mu_{mt})\gamma_m I_m + (1-\mu_{mt})\rho_{\theta_m}} \\ &= \frac{(t+1)\delta \overline{x}_m + \frac{(\alpha_m I_m \mu_{mt} \gamma_m + (1-\mu_{mt})\rho_{\theta_m})(\rho_m + \gamma_m I_m)}{\alpha_m I_m \gamma_m}\overline{c}_m}{M} \end{aligned}$$

■

Proof of Proposition 3.

The expected utility of informed investors is given by

$$\begin{aligned} U^i_{t,I} &= E(u^i_{tI} \mid \{S^i_{mt}, Y^i_{mt}\}) \\ &= E(-e^{-\delta W^i_{tI}} \mid \{S^i_{mt}, Y^i_{mt}\}) \\ i.e. W^i_{tI} &= m^i_{t-1} + \sum_{m=1}^{M} (v_m - p_{mt} - c^i_{mt}) z^i_{mt,I} \end{aligned}$$

By moment generating function of $x \sim N(\mu, \sigma^2)$, we have

$$m(t) = E(\exp(tx)) = \exp(t\mu + \frac{1}{2}\sigma^2 t)$$

So,

$$U^i_{t,I} = -\exp(-\delta m^i_{t-1} - \frac{(E(v^i_{mt} \mid \{S^i_{mt}, Y^i_{mt}\}) - p_{mt} - c^i_{mt})^2}{2\rho^{-1}_{mI}\delta^{2-1}}) \tag{A6}$$

$$E(U^i_{t,I} \mid \theta^i_{mt}) = -\exp(-\delta m^i_{t-1})E(e^{-\frac{(E(v^i_{mt} \mid \{S^i_{mt}, Y^i_{mt}\}) - p_{mt} - c^i_{mt})^2}{2\rho^{-1}_{mI}\delta^{2-1}}} \mid \theta^i_{mt}) \tag{A7}$$

We define $z_i = \frac{E(v^i_{mt} \mid \{S^i_{mt}, Y^i_{mt}\}) - p_{mt} - c^i_{mt}}{\sqrt{n}}$, and $n = Var(v^i_{mt} \mid \{S^i_{mt}, Y^i_{mt}\} \mid \theta^i_{mt})$

By the Conditional expected variance formula and (1), (6), $Var(Y) = E(Var(Y \mid X)) + Var(E(Y \mid X))$

$E(v^i_{mt} \mid \{S^i_{mt}, Y^i_{mt}\}) = \overline{v}^i_m = \frac{\rho_m \overline{v}_m + \gamma_m 1 S^i_{mt} + \gamma_m 1 Y^i_{mt}}{\rho_m + \gamma_m I_m}, Var(v^i_{mt} \mid \{S^i_{mt}, Y^i_{mt}\})^{-1} = \rho^i_{mI} = \rho_m + \gamma_m I_m$

$$\begin{aligned} E(v^i_{mt} \quad &\mid \quad \{Y^i_{mt}, \theta^i_{mt}\}) = \overline{v}^i_m = \frac{\rho_m \overline{v}_m + \gamma_m 1 Y^i_{mt} + \rho_{\theta_m}\theta^i_{mt}}{\rho_m + \gamma_m(1-\alpha_m)I_m + \rho_{\theta_m}} \\ Var(v^i_{mt} \quad &\mid \quad \{Y^i_{mt}, \theta^i_{mt}\})^{-1} = \rho^i_{mU} = \rho_m + \gamma_m(1-\alpha_m)I_m + \rho_{\theta_m} \end{aligned}$$

We get $n = Var(v^i_{mt} \mid \{S^i_{mt}, Y^i_{mt}\} \mid \theta^i_{mt}) = \rho^{i-1}_{mU} - \rho^{i-1}_{mI}$

If z_i follows the normal distribution, then $E(e^{-tz_i^2} \mid \theta) = \frac{1}{\sqrt{1+2t}} \exp(\frac{-(E(z_i|\theta))^2 t}{1+2t} \mid \theta)$

According to the formula above, we get

$E(e^{-\frac{(E(v^i_{mt} \mid \{S^i_{mt}, Y^i_{mt}\}) - p_{mt})^2}{2\rho^{-1}_{mI}\delta^{2-1}}} \mid \theta^i_{mt}) = \sqrt{\frac{\rho^{i-1}_{mU}}{\rho^{i-1}_{mI}}} \exp(\frac{-(E(z_i|\theta))^2 n}{2\rho^{i-1}_{mU}\delta^{2-1}} \mid \theta)$

$= \sqrt{\frac{\rho^{i-1}_{mU}}{\rho^{i-1}_{mI}}} \exp(\frac{-(E(v^i_{mt}|\theta^i_{mt}) - p_{mt} - c^i_{mt})^2}{2\rho^{i-1}_{mU}\delta^{2-1}} \mid \theta)$

$= \sqrt{\frac{\rho^{i-1}_{mU}}{\rho^{i-1}_{mI}}} \exp(\frac{-(E(v^i_{mt}|\theta^i_{mt}) - p_{mt})^2 - {c^i_{mt}}^2 + 2c^i_{mt}((E(v^i_{mt}|\theta^i_{mt}) - p_{mt})}{2\rho^{i-1}_{mU}\delta^{2-1}} \mid \theta)$

$= \sqrt{\frac{\rho^{i-1}_{mU}}{\rho^{i-1}_{mI}}} \exp(\frac{-(E(v^i_{mt}|\theta^i_{mt}) - p_{mt}|\theta)^2}{2\rho^{i-1}_{mU}\delta^{2-1}}) \exp(\frac{-{c^i_{mt}}^2 + 2c^i_{mt}(E(v^i_{mt}|\theta^i_{mt}) - p_{mt}|\theta)}{2\rho^{i-1}_{mU}\delta^{2-1}})$

So $U^i_{t,U} = E(u^i_{t,U} \mid \theta^i_{mt}) = -\exp(-\delta m^i_{t-1})\sqrt{\frac{\rho^{i-1}_{mU}}{\rho^{i-1}_{mI}}} \exp(\frac{-((E(v^i_{mt}|\theta^i_{mt}) - p_{mt})|\theta)^2}{2\rho^{i-1}_{mU}\delta^{2-1}})$

By (1)-(6) and proposition 1, we have

$$\begin{aligned} E(v^i_{mt} \quad \mid \quad \theta^i_{mt}) - p_{mt} &= E(\frac{\rho_m \overline{v}_m + \gamma_m 1 Y^i_{mt} + \rho_{\theta_m}\theta^i_{mt}}{\rho_m + \gamma_m(1-\alpha_m)I_m + \rho_{\theta_m}} \mid \theta^i_{mt}) - p_{mt} \\ &= (\frac{\rho_{\theta_m}}{(\rho_m + \gamma_m(1-\alpha_m)I_m + \rho_{\theta_m})b_t\alpha_m I_m} - 1)p_{mt} \\ &= \frac{-\mu_{mt}(\alpha_m I_m \gamma_m - \rho_{\theta_m})(\rho_m + (1-\alpha_m)\gamma_m I_m)}{(\rho_m + \gamma_m(1-\alpha_m)I_m + \rho_{\theta_m})(\mu_{mt}\alpha_m I_m \gamma_m + (1-\mu_{mt})\rho_{\theta_m})} p_{mt} \\ &= Lp_{mt} \\ i.e.L &= \frac{-\mu_{mt}(\alpha_m I_m \gamma_m - \rho_{\theta_m})(\rho_m + (1-\alpha_m)\gamma_m I_m)}{(\rho_m + \gamma_m(1-\alpha_m)I_m + \rho_{\theta_m})(\mu_{mt}\alpha_m I_m \gamma_m + (1-\mu_{mt})\rho_{\theta_m})} \\ E(E(v^i_{mt} \quad \mid \quad \theta^i_{mt}) - p_{mt}) &= LE(p_{mt}) \end{aligned}$$

Plug into A7,

$$\begin{aligned}
E(U_{t,I}^{i} \quad | \quad p_{mt}) &= -\exp(-\delta m_{t-1}^{i})\sqrt{\frac{\rho_{mU}^{i-1}}{\rho_{mI}^{i-1}}}\exp(\frac{-(E(v_{mt}^{i} \mid \theta_{mt}^{i}) - p_{mt})^{2}}{2\rho_{mU}^{i-1}}) \\
&\quad \exp(\frac{-{c_{mt}^{i}}^{2} + 2c_{mt}^{i}(E(v_{mt}^{i} \mid \theta_{mt}^{i}) - p_{mt})}{2\rho_{mU}^{i-1}}) \\
&= -\exp(-\delta m_{t-1}^{i})\sqrt{\frac{\rho_{mU}^{i-1}}{\rho_{mI}^{i-1}}}\exp(\frac{-(Lp_{mt})^{2} - {c_{mt}^{i}}^{2} + 2c_{mt}^{i}Lp_{mt}}{2\rho_{mU}^{i-1}})
\end{aligned}$$

By (11),

$$\underset{\mu_{mt},\gamma_m}{Max}\ \mu_{mt}U_{tI}^{i} + (1-\mu_{mt})U_{tU}^{i}$$

Plug in (A7) and (A8), we get

$$\exp(\frac{-{c_{mt}^{i}}^{2} + 2c_{mt}^{i}(E(v_{mt}^{i} \mid \theta_{mt}^{i}) - p_{mt} \mid \theta)}{2\rho_{mU}^{i-1}\delta^{2-1}}) = 1$$

That is

$$\begin{aligned}
\gamma_m^{*} &= Max\{0, \gamma_m^{*} \left| \exp(\frac{-C^{m}(\gamma_m)^{2} + 2C^{m}(\gamma_m)(E(v_{mt}^{i} \mid \theta_{mt}^{i}) - p_{mt} \mid \theta)}{2(\rho_m + \gamma_m(1-\alpha_m)I_m + \rho_{\theta_m})^{-1}\delta^{2-1}}) = 1\right.\} \\
&= Max\{0, \gamma_m \left| \exp(\frac{-C^{m}(\gamma_m)^{2} + 2C^{m}(\gamma_m)(LE(p_{mt}))}{2(\rho_m + \gamma_m(1-\alpha_m)I_m + \rho_{\theta_m})^{-1}\delta^{2-1}}) = 1\right.\}
\end{aligned}$$

Optimal cost of information acquisitions $C_m^{*} = C^{m}(\gamma_m^{*})$

By (11), we could get

$$\mu_{mt}^{*} = \frac{\frac{\partial U_{t,U}^{i}}{\partial \gamma_m}}{\frac{\partial U_{t,U}^{i}}{\partial \gamma_m} - \frac{\partial U_{t,I}^{i}}{\partial \gamma_m}} = G(\gamma_m^{*})$$

Therefore, we get the optimal level of precision of private information γ_m^{*}, optimal cost of information acquisitions C_m^{*} and the equilibrium fraction of informed investors μ_m^{*} for asset m ■

Proof of Proposition 4

By proposition 3, we know if investor pays the cost of acquiring private information, his expected indirect utility should be at least larger than those uninformed. That is: $U_{tI}^{i} \geqslant U_{tU}^{i}$

By A7 and A8, we could get

$$0 < C^{m}(\gamma_m) \leqslant C_m^{*}$$

Since $C^{m}(.)$ is strictly increasing, we get $0 < \gamma_m \leqslant \gamma_m^{*}$

So if the precision level of private information is not more than γ_m^{*}, investor will choose to be informed; otherwise, he will stay uninformed. ■

Proof of Proposition 5

We define $Var(v^i_{mt} \mid p_{mt})$ and $Var(v^i_{mt} - p_{mt})$ as a measure for the level of informativeness of price and the quality of the price respectively. By proposition 3, we get $Var(v^i_{mt} \mid p_{mt}) = \frac{1}{\rho_m(1+\frac{\eta_m}{\delta(1+A)})}, A = \frac{(1-\mu_{mt})\rho_{\theta_m}}{\alpha_m I_m \mu_{mt} \gamma_m}$

$$\begin{aligned} Var(v^i_{mt} - p_{mt}) &= L^2(\frac{a_t^2}{\rho_m} + \frac{d_t^2}{\eta_m}) \\ L &= \frac{1}{(\frac{\rho_m+\gamma_m(1-\alpha_m)I_m+\rho_{\theta_m}}{\rho_{\theta_m}})(\frac{\mu_{mt}\alpha_m I_m \gamma_m+(1-\mu_{mt})\rho_{\theta_m}}{M})} - 1 \end{aligned}$$

We compute

$$\begin{aligned} \frac{\partial A}{\partial \gamma_m} &= \frac{(1-\mu_{mt})\rho_{\theta_m}}{\mu_{mt}\alpha_m I_m \gamma_m}(\rho_{\theta_m}(\frac{1}{\alpha_m I_m \gamma_m^2} + \\ &\quad \frac{2\delta^2}{(\alpha_m I_m \mu_m)^2 \eta_m \gamma_m^3}) - \frac{1}{\gamma_m}) \\ &> 0 \end{aligned}$$

Also we could get $\frac{\partial L}{\partial \alpha_m} < 0$, $\frac{\partial L}{\partial \gamma_m} < 0$

(i) If the informed investor acquires more private information, that is, α_m increases,

$$\begin{aligned} \frac{\partial Var(v^i_{mt} \mid p_{mt})}{\partial \alpha_m} &= \frac{\eta_m \frac{\partial A}{\partial \alpha_m}}{\rho_m(1+\frac{\eta_m}{\delta(1+A)})^2\delta(1+A)^2} \\ &> 0 \end{aligned}$$

$$\frac{\partial Var(v^i_{mt} - p_{mt})}{\partial \alpha_m} < 0$$

(ii) If he acquires a higher level of precision of private information, that is, γ_m increases,

$$\begin{aligned} \frac{\partial Var(v^i_{mt} \mid p_{mt})}{\partial \gamma_m} &= \frac{\eta_m \frac{\partial A}{\partial \gamma_m}}{\rho_m(1+\frac{\eta_m}{\delta(1+A)})^2\delta(1+A)^2} \\ &> 0 \end{aligned}$$

$$\frac{\partial Var(v^i_{mt} - p_{mt})}{\partial \gamma_m} < 0$$

■

Proof of Proposition 6.

By (2), (7) and proposition 1, we get

$$\begin{aligned} z^i_{mt,I} - z^i_{mt,U} &= \frac{\rho_m \overline{v}_m + \gamma_m 1S^i_{mt} + \gamma_m 1Y^i_{mt} - (p_{mt} + c^i_{mt})(\rho_m + \gamma_m I_m)}{\delta} - \\ &\quad \frac{\rho_m \overline{v}_m + \gamma_m 1Y^i_{mt} + \rho_{\theta_m}\theta^i_{mt} - p_{mt}(\rho_m + \gamma_m(1-\alpha_m)I_m + \rho_{\theta_m})}{\delta} \\ &= \delta^{-1}\{(\alpha_m I_m \gamma_m - \rho_{\theta_m})[\frac{(\rho_m + (1-\alpha_m)\gamma_m I_m)}{M}\frac{1S^i_{mt}}{\alpha_m I_m} - \frac{\rho_m}{M}\overline{v}_m \\ &\quad -\frac{(1-\alpha_m)I_m\gamma_m}{M}\frac{1Y^i_{mt}}{(1-\alpha_m)I_m}] + \frac{\delta\rho_{\theta_m}(\rho_m + \gamma_m I_m)}{\alpha_m I_m \gamma_m \mu_{mt} M}(x_{mt} - \overline{x}_m) \\ &\quad + \frac{\delta(\alpha_m I_m \gamma_m - \rho_{\theta_m})}{M}(X_{m,t} - \frac{(\rho_m + \gamma_m I_m)(\rho_m + (1-\alpha_m)\gamma_m I_m)}{\delta \alpha_m I_m \gamma_m}c^i_{mt})\} \end{aligned} \tag{A10}$$

Good private information raises the informed investor's holding of asset m relative to the uninformed while bad private information has the opposite effects. Thus on average the informed trade more of the risky asset m than do the uninformed.

$$\frac{\partial(z^i_{mt,I} - z^i_{mt,U})}{\partial\frac{1S^i_{mt}}{\alpha_m I_m}} > 0$$

How does the public information affect the informed and uninformed's portfolios? Using comparative analysis, we have

$$\frac{\partial(z^i_{mt,I} - z^i_{mt,U})}{\partial\frac{1Y^i_{mt}}{(1-\alpha_m)I_m}} < 0$$

$$\begin{aligned} E(z^i_{mt,I} - z^i_{mt,U}) &= \delta^{-1}E\{(\alpha_m I_m \gamma_m - \rho_{\theta_m})[\frac{(\rho_m + (1-\alpha_m)\gamma_m I_m)}{M}\frac{1S^i_{mt}}{\alpha_m I_m} - \frac{\rho_m}{M}\overline{v}_m \\ &\quad -\frac{(1-\alpha_m)I_m\gamma_m}{M}\frac{1Y^i_{mt}}{(1-\alpha_m)I_m}] + \frac{\delta\rho_{\theta_m}(\rho_m + \gamma_m I_m)}{\alpha_m I_m \gamma_m \mu_{mt} M}(x_{mt} - \overline{x}_m) \\ &\quad + \frac{\delta(\alpha_m I_m \gamma_m - \rho_{\theta_m})}{M}(X_{m,t} - \frac{(\rho_m + \gamma_m I_m)(\rho_m + (1-\alpha_m)\gamma_m I_m)}{\delta \alpha_m I_m \gamma_m}c^i_{mt})\} \end{aligned} \tag{A11}$$

We are assuming signals about private information are more accurate than public information. Investors holding private information know more about the true value of the asset returns.

We define the average asset holding when there are no information as a benchmark.

$$\begin{aligned} E(z^i_{mt,I} - z^i_{mt,U} &\mid \text{No useful signals}) \\ &= \frac{(\alpha_m I_m \gamma_m - \rho_{\theta_m})}{M}E(X_{m,t} - \frac{(\rho_m + \gamma_m I_m)(\rho_m + (1-\alpha_m)\gamma_m I_m)}{\delta \alpha_m I_m \gamma_m}c^i_{mt}) \end{aligned} \tag{A12}$$

(1) Private information and public information are consistent, i.e. private signals and public signals contain good news or bad news.

(a) If there are good private and public information, we have $\frac{1S^i_{mt}}{\alpha_m I_m} > \overline{v}_m$ and $\frac{1Y^i_{mt}}{(1-\alpha_m)I_m} > \overline{v}_m$. Informed investors know more since they have private information, i.e. $\frac{1S^i_{mt}}{\alpha_m I_m} > \frac{1Y^i_{mt}}{(1-\alpha_m)I_m}$. By (A7) and (A8), we get

$$\frac{(\rho_m + (1-\alpha_m)\gamma_m I_m)}{M}\frac{1S^i_{mt}}{\alpha_m I_m} - \frac{\rho_m}{M}\overline{v}_m - \frac{(1-\alpha_m)I_m\gamma_m}{M}\frac{1Y^i_{mt}}{(1-\alpha_m)I_m} > 0$$

We assume the aggregate supply of the asset is larger than information cost. If the information cost for some investors are so large, then they will choose not to be informed at the beginning.

$$\begin{aligned}
& E(z^i_{mt,I} - z^i_{mt,U} \mid \frac{1S^i_{mt}}{\alpha_m I_m} > \frac{1Y^i_{mt}}{(1-\alpha_m)I_m} > \overline{v}_m) \\
> \quad & E\frac{\delta(\alpha_m I_m \gamma_m - \rho_{\theta_m})}{M}(X_{m,t} - \frac{(\rho_m + \gamma_m I_m)(\rho_m + (1-\alpha_m)\gamma_m I_m)}{\delta\alpha_m I_m \gamma_m}c^i_{mt}) \\
= \quad & E(z^i_{mt,I} - z^i_{mt,U} \mid \text{No useful signals})
\end{aligned}$$

So informed investors will hold more of the risky asset than the uninformed when both private and public information contain good news.

(b) If there are bad private and public information, we have $\frac{1S^i_{mt}}{\alpha_m I_m} < \overline{v}_m$ and $\frac{1Y^i_{mt}}{(1-\alpha_m)I_m} < \overline{v}_m$. Informed investors know more since they have private information, i.e. $\frac{1S^i_{mt}}{\alpha_m I_m} < \frac{1Y^i_{mt}}{(1-\alpha_m)I_m}$. By (A7), we get $\frac{(\rho_m+(1-\alpha_m)\gamma_m I_m)}{M}\frac{1S^i_{mt}}{\alpha_m I_m} - \frac{\rho_m}{M}\overline{v}_m - \frac{(1-\alpha_m)I_m\gamma_m}{M}\frac{1Y^i_{mt}}{(1-\alpha_m)I_m} < 0$

$$E\frac{(\rho_m + (1-\alpha_m)\gamma_m I_m)}{M}\frac{1S^i_{mt}}{\alpha_m I_m} - \frac{\rho_m}{M}\overline{v}_m - \frac{(1-\alpha_m)I_m\gamma_m}{M}\frac{1Y^i_{mt}}{(1-\alpha_m)I_m} = -\varepsilon$$

Since there are bad news, informed investors will choose to hold less and diversify their portforlio. Informed investors pay information cost to acquire higher risk premium. If both investors lose money, Informed investors lose less.

$E(z^i_{mt,I} - z^i_{mt,U} \mid \frac{1S^i_{mt}}{\alpha_m I_m} < \frac{1Y^i_{mt}}{(1-\alpha_m)I_m} < \overline{v}_m)$
$= E\frac{\delta(\alpha_m I_m\gamma_m - \rho_{\theta_m})}{M}(X_{m,t} - \frac{(\rho_m+\gamma_m I_m)(\rho_m+(1-\alpha_m)\gamma_m I_m)}{\delta\alpha_m I_m\gamma_m}c^i_{mt}) - (\alpha_m I_m \gamma_m - \rho_{\theta_m})\varepsilon$
$= E(z^i_{mt,I} - z^i_{mt,U}$ |No useful signals$) - (\alpha_m I_m\gamma_m - \rho_{\theta_m})\varepsilon$
$< E(z^i_{mt,I} - z^i_{mt,U}$ |No useful signals$)$

So informed investors will short more of the risky asset than the uninformed when both private and public information contain bad news.

(2) Private information and public information are inconsistent, i.e. private signals and public signals contain different information.

(c) If there are good private signals and bad public signals, we have $\frac{1S^i_{mt}}{\alpha_m I_m} > \overline{v}_m$ and $\frac{1Y^i_{mt}}{(1-\alpha_m)I_m} < \overline{v}_m$. Obviously, the informed investors will have higher expected returns since the uninformed will hold less and informed will hold more according to the different signals about the assets.

$$\frac{(\rho_m + (1-\alpha_m)\gamma_m I_m)}{M}\frac{1S^i_{mt}}{\alpha_m I_m} - \frac{\rho_m}{M}\overline{v}_m - \frac{(1-\alpha_m)I_m\gamma_m}{M}\frac{1Y^i_{mt}}{(1-\alpha_m)I_m} > 0$$

We get

$$\begin{aligned} & E(z^i_{mt,I} - z^i_{mt,U} \mid \frac{1S^i_{mt}}{\alpha_m I_m} > \overline{v}_m > \frac{1Y^i_{mt}}{(1-\alpha_m)I_m}) \\ > \quad & E\frac{\delta(\alpha_m I_m \gamma_m - \rho_{\theta_m})}{M}(X_{m,t} - \frac{(\rho_m + \gamma_m I_m)(\rho_m + (1-\alpha_m)\gamma_m I_m)}{\delta\alpha_m I_m \gamma_m}c^i_{mt}) \\ = \quad & E(z^i_{mt,I} - z^i_{mt,U} \mid \text{No useful signals}) \end{aligned}$$

So informed investors will hold more of the risky asset than the uninformed when private information is good news and public information contain bad news.

(d) If there are bad private signals and good public signals, we have $\frac{1S^i_{mt}}{\alpha_m I_m} < \overline{v}_m$ and $\frac{1Y^i_{mt}}{(1-\alpha_m)I_m} > \overline{v}_m$. Informed investors will choose to hold less and the uninformed choose to hold more according to the different signals about the assets. Then we get $\frac{(\rho_m+(1-\alpha_m)\gamma_m I_m)}{M}\frac{1S^i_{mt}}{\alpha_m I_m} - \frac{\rho_m}{M}\overline{v}_m - \frac{(1-\alpha_m)I_m\gamma_m}{M}\frac{1Y^i_{mt}}{(1-\alpha_m)I_m} < 0$

$$E\frac{(\rho_m + (1-\alpha_m)\gamma_m I_m)}{M}\frac{1S^i_{mt}}{\alpha_m I_m} - \frac{\rho_m}{M}\overline{v}_m - \frac{(1-\alpha_m)I_m\gamma_m}{M}\frac{1Y^i_{mt}}{(1-\alpha_m)I_m} = -\varepsilon$$

If both investors lose money, Informed investors lose less. So informed investors have higher risk premium.

$$\begin{aligned} & E(z^i_{mt,I} - z^i_{mt,U} \mid \frac{1S^i_{mt}}{\alpha_m I_m} < \overline{v}_m < \frac{1Y^i_{mt}}{(1-\alpha_m)I_m}) \\ = \quad & E\frac{\delta(\alpha_m I_m \gamma_m - \rho_{\theta_m})}{M}(X_{m,t} - \frac{(\rho_m + \gamma_m I_m)(\rho_m + (1-\alpha_m)\gamma_m I_m)}{\delta\alpha_m I_m \gamma_m}c^i_{mt}) \\ & -(\alpha_m I_m \gamma_m - \rho_{\theta_m})\varepsilon \\ = \quad & E(z^i_{mt,I} - z^i_{mt,U} \mid \text{No useful signals}) - (\alpha_m I_m \gamma_m - \rho_{\theta_m})\varepsilon \\ < \quad & E(z^i_{mt,I} - z^i_{mt,U} \mid \text{No useful signals}) \end{aligned}$$

So informed investors will short more of the risky asset than the uninformed when private information is bad news and public information contain good news.■

Proof of Proposition 7.

By (1)-(5), we can get

$$\begin{aligned}
E(Ev^i_{mt,I} &\mid \{S^i_{mt}, Y^i_{mt}\} - Ev^i_{mt,U} \mid \{Y^i_{mt}, \theta^i_{mt}\}) = E(\overline{v}^i_{m,I} - \overline{v}^i_{m,U}) \qquad \text{(A13)}\\
&= E(\frac{\rho_m\overline{v}_m + \gamma_m 1S^i_{mt} + \gamma_m 1Y^i_{mt}}{\rho_m + \gamma_m I_m} - \frac{\rho_m\overline{v}_m + \gamma_m 1Y^i_{mt} + \rho_{\theta_m}\theta^i_{mt}}{\rho_m + \gamma_m(1-\alpha_m)I_m + \rho_{\theta_m}})\\
&= E\frac{\begin{array}{c}(\rho_m\overline{v}_m + \gamma_m 1Y^i_{mt})(\rho_{\theta_m} - \alpha_m I_m\gamma_m) + \gamma_m 1S^i_{mt}(\rho_m + \gamma_m(1-\alpha_m)I_m + \rho_{\theta_m})\\ -\rho_{\theta_m}(\frac{1S^i_{mt}}{\alpha_m I_m} - \frac{d_t}{b_t\alpha_m I_m}(x_{mt} - \overline{x}_m) - \frac{f_t c^i_{mt}}{b_t\alpha_m I_m})(\rho_m + \gamma_m I_m)\end{array}}{(\rho_m + \gamma_m I_m)(\rho_m + \gamma_m(1-\alpha_m)I_m + \rho_{\theta_m})}\\
&= E\frac{\begin{array}{c}(\alpha_m I_m\gamma_m - \rho_{\theta_m})(\gamma_m 1S^i_{mt}\frac{\rho_m + (1-\alpha_m)I_m\gamma_m}{\alpha_m I_m\gamma_m} - \rho_m\overline{v}_m - \gamma_m 1Y^i_{mt}) +\\ \frac{\rho_{\theta_m}\delta(\rho_m + \gamma_m I_m)}{\mu_{mt}\gamma_m\alpha_m I_m}(x_{mt} - \overline{x}_m) + \frac{\rho_{\theta_m}(\rho_m + \gamma_m I_m)^2}{\alpha_m I_m\gamma_m}c^i_{mt}\end{array}}{(\rho_m + \gamma_m I_m)(\rho_m + \gamma_m(1-\alpha_m)I_m + \rho_{\theta_m})}
\end{aligned}$$

We are assuming signals about private information are more accurate than public information. Investors holding private information know more about the true value of the asset returns.

We define the average asset return when there are no information as a benchmark.

$$\begin{aligned}
E(Ev^i_{mt,I} &\mid \{S^i_{mt}, Y^i_{mt}\} - Ev^i_{mt,U} \mid \{Y^i_{mt}, \theta^i_{mt}\} \mid \text{No useful signals}) \qquad \text{(A14)}\\
&= E\frac{\rho_{\theta_m}(\rho_m + \gamma_m I_m)c^i_{mt}}{\alpha_m I_m\gamma_m(\rho_m + \gamma_m(1-\alpha_m)I_m + \rho_{\theta_m})}
\end{aligned}$$

(1) Private information and public information are consistent, i.e. private signals and public signals are both containing good news or bad news.

(a) If there are good private and public information, we have $\frac{1S^i_{mt}}{\alpha_m I_m} > \overline{v}_m$ and $\frac{1Y^i_{mt}}{(1-\alpha_m)I_m} > \overline{v}_m$. Informed investors know more since they have private information, i.e. $\frac{1S^i_{mt}}{\alpha_m I_m} > \frac{1Y^i_{mt}}{(1-\alpha_m)I_m}$. By (A9), we get $\gamma_m 1S^i_{mt}\frac{\rho_m + (1-\alpha_m)I_m\gamma_m}{\alpha_m I_m\gamma_m} - \rho_m\overline{v}_m - \gamma_m 1Y^i_{mt} > 0$

$$\begin{aligned}
E\{(Ev^i_{mt,I} &\mid \{S^i_{mt}, Y^i_{mt}\} - Ev^i_{mt,U} \mid \{Y^i_{mt}, \theta^i_{mt}\}) \mid \frac{1S^i_{mt}}{\alpha_m I_m} > \frac{1Y^i_{mt}}{(1-\alpha_m)I_m} > \overline{v}_m\}\\
&> \frac{\rho_{\theta_m}(\rho_m + \gamma_m I_m)\overline{c}_m}{\alpha_m I_m\gamma_m(\rho_m + \gamma_m(1-\alpha_m)I_m + \rho_{\theta_m})}\\
&= E(Ev^i_{mt,I} \mid \{S^i_{mt}, Y^i_{mt}\} - Ev^i_{mt,U} \mid \{Y^i_{mt}, \theta^i_{mt}\} \mid \text{No useful signals})\\
&> 0
\end{aligned}$$

So informed investors will hold more of the risky asset than the uninformed when both private and public information contain good news. Informed investors get higher average expected return than the uninformed.

(b) If there are bad private and public information, we have $\frac{1S^i_{mt}}{\alpha_m I_m} < \overline{v}_m$ and $\frac{1Y^i_{mt}}{(1-\alpha_m)I_m} < \overline{v}_m$. Informed investors know more since they have private information, i.e. $\frac{1S^i_{mt}}{\alpha_m I_m} < \frac{1Y^i_{mt}}{(1-\alpha_m)I_m}$. By

(A8), we get $\gamma_m 1S^i_{mt}\frac{\rho_m+(1-\alpha_m)I_m\gamma_m}{\alpha_m I_m\gamma_m} - \rho_m\overline{v}_m - \gamma_m 1Y^i_{mt} < 0$

$$E\gamma_m 1S^i_{mt}\frac{\rho_m+(1-\alpha_m)I_m\gamma_m}{\alpha_m I_m\gamma_m} - \rho_m\overline{v}_m - \gamma_m 1Y^i_{mt} = -\varepsilon$$

Since there are bad news, informed investors will choose to hold less and diversify their portforlio. Informed investors pay information cost to acquire higher risk premium. If both investors lose money, Informed investors lose less.

$$\begin{aligned}
E\{(Ev^i_{mt,I} \quad &| \quad \{S^i_{mt}, Y^i_{mt}\} - Ev^i_{mt,U} \mid \{Y^i_{mt}, \theta^i_{mt}\}) \mid \frac{1S^i_{mt}}{\alpha_m I_m} < \frac{1Y^i_{mt}}{(1-\alpha_m)I_m} < \overline{v}_m\} \\
&= \quad \frac{\rho_{\theta_m}(\rho_m+\gamma_m I_m)\overline{c}_m - \frac{(\alpha_m I_m\gamma_m - \rho_{\theta_m})}{(\rho_m+\gamma_m I_m)}\varepsilon}{\alpha_m I_m\gamma_m(\rho_m+\gamma_m(1-\alpha_m)I_m+\rho_{\theta_m})} \\
&< \quad E(Ev^i_{mt,I} \mid \{S^i_{mt}, Y^i_{mt}\} - Ev^i_{mt,U} \mid \{Y^i_{mt}, \theta^i_{mt}\} \mid \text{No useful signals})
\end{aligned}$$

So informed investors will hold less of the risky asset than the uninformed when both private and public information contain bad news. Both informed and uninformed investors lose money for the asset m but the average expected return is still higher for the informed investors.

(2) Private information and public information are inconsistent, i.e. private signals and public signals contain different information.

(c) If there are good private signals and bad public signals, we have $\frac{1S^i_{mt}}{\alpha_m I_m} > \overline{v}_m$ and $\frac{1Y^i_{mt}}{(1-\alpha_m)I_m} < \overline{v}_m$. Obviously, the informed investors will have higher expected returns since the uninformed will hold less and informed will hold more according to the different signals about the assets. Since $\gamma_m 1S^i_{mt}\frac{\rho_m+(1-\alpha_m)I_m\gamma_m}{\alpha_m I_m\gamma_m} - \rho_m\overline{v}_m - \gamma_m 1Y^i_{mt} > 0$, we get

$$\begin{aligned}
E\{(Ev^i_{mt,I} \quad &| \quad \{S^i_{mt}, Y^i_{mt}\} - Ev^i_{mt,U} \mid \{Y^i_{mt}, \theta^i_{mt}\}) \mid \frac{1S^i_{mt}}{\alpha_m I_m} > \overline{v}_m > \frac{1Y^i_{mt}}{(1-\alpha_m)I_m}\} \\
&> \quad \frac{\rho_{\theta_m}(\rho_m+\gamma_m I_m)\overline{c}_m}{\alpha_m I_m\gamma_m(\rho_m+\gamma_m(1-\alpha_m)I_m+\rho_{\theta_m})} \\
&= \quad E(Ev^i_{mt,I} \mid \{S^i_{mt}, Y^i_{mt}\} - Ev^i_{mt,U} \mid \{Y^i_{mt}, \theta^i_{mt}\} \mid \text{No useful signals}) \\
&> \quad 0
\end{aligned}$$

So informed investors will hold more of the risky asset than the uninformed when private information is good news and public information contain bad news. Informed investors get higher average expected return than the uninformed.

(d) If there are bad private signals and good public signals, we have $\frac{1S^i_{mt}}{\alpha_m I_m} < \overline{v}_m$ and $\frac{1Y^i_{mt}}{(1-\alpha_m)I_m} > \overline{v}_m$. Informed investors will choose to hold less and the uninformed choose to hold more according to the different signals about the assets. Then we get

$$\gamma_m 1S^i_{mt}\frac{\rho_m+(1-\alpha_m)I_m\gamma_m}{\alpha_m I_m\gamma_m} - \rho_m\overline{v}_m - \gamma_m 1Y^i_{mt} < 0$$

$$E\gamma_m 1S^i_{mt}\frac{\rho_m+(1-\alpha_m)I_m\gamma_m}{\alpha_m I_m\gamma_m}-\rho_m\overline{v}_m-\gamma_m 1Y^i_{mt}=-\varepsilon$$

If both investors lose money, Informed investors lose less. So informed investors have higher risk premium.

$$\begin{aligned} E\{(Ev^i_{mt,I} \quad &| \quad \{S^i_{mt},Y^i_{mt}\}-Ev^i_{mt,U}\mid\{Y^i_{mt},\theta^i_{mt}\})\mid\frac{1S^i_{mt}}{\alpha_m I_m}<\overline{v}_m<\frac{1Y^i_{mt}}{(1-\alpha_m)I_m}\} \\ &= \quad \frac{\rho_{\theta_m}(\rho_m+\gamma_m I_m)\overline{c}_m-\frac{(\alpha_m I_m\gamma_m-\rho_{\theta_m})}{(\rho_m+\gamma_m I_m)}\varepsilon}{\alpha_m I_m\gamma_m(\rho_m+\gamma_m(1-\alpha_m)I_m+\rho_{\theta_m})} \\ &< \quad E(Ev^i_{mt,I}\mid\{S^i_{mt},Y^i_{mt}\}-Ev^i_{mt,U}\mid\{Y^i_{mt},\theta^i_{mt}\}\mid \text{No useful signals}) \end{aligned}$$

So informed investors will hold less of the risky asset than the uninformed when private information is bad news and public information contain good news. Both informed and uninformed investors lose money for the asset m but the average expected return is still higher for the informed investors.

So we have

$$E(Ev^i_{mt,I}\mid\{S^i_{mt},Y^i_{mt}\}-Ev^i_{mt,U}\mid\{Y^i_{mt},\theta^i_{mt}\})>0$$

■

Proof of Proposition 8.

By proposition 1 and 2, we get

$cov(v_{mt}-p_{mt},v_{nt}-p_{nt})=E(v_{mt}-p_{mt}-E(v_{mt}-p_{mt}))(v_{nt}-p_{nt}-E\,(v_{nt}-p_{nt})$

$=E(v_{mt}-(a_t\overline{v}_m+b_t1S^i_{mt}+c_t1Y^i_{mt}-d_tx_{mt}+e_t\overline{x}_m-g_tX_{m,t-1}-f_tc^i_{mt})$
$-(\frac{(t+1)\delta\overline{x}_m+\frac{(\alpha_m I_m\mu_{mt}\gamma_m+(1-\mu_{mt})\rho_{\theta_m})(\rho_m+\gamma_m I_m)}{\alpha_m I_m\gamma_m}\overline{c}_m}{\rho_m+(1-\alpha_m+\alpha_m\mu_{mt})\gamma_m I_m+(1-\mu_{mt})\rho_{\theta_m}})(v_{nt}-(a_t\overline{v}_n+b_t1S^i_{nt}+c_t1Y^i_{nt}-d_tx_{nt}+e_t\overline{x}_n-$
$g_tX_{n,t-1}-f_tc^i_{nt})$
$-\frac{(t+1)\delta\overline{x}_n+\frac{(\alpha_n I_n\mu_{nt}\gamma_n+(1-\mu_{nt})\rho_{\theta_n})(\rho_n+\gamma_n I_n)}{\alpha_n I_n\gamma_n}\overline{c}_n}{\rho_n+(1-\alpha_n+\alpha_n\mu_{nt})\gamma_n I_n+(1-\mu_{nt})\rho_{\theta_n}})$

$cov(v_{mt}-p_{mt},v_{nt}-p_{nt})$
$=\frac{(\rho_m+\gamma_m I_m)(\mu_{mt}\alpha_m I_m\gamma_m+(1-\mu_{mt})\rho_{\theta_m})}{\alpha_m I_m\gamma_m(\rho_m+(1-\alpha_m+\alpha_m\mu_{mt})\gamma_m I_m+(1-\mu_{mt})\rho_{\theta_m})}\frac{(\rho_n+\gamma_n I_n)(\mu_{nt}\alpha_n I_n\gamma_n+(1-\mu_{nt})\rho_{\theta_n})}{\alpha_n I_n\gamma_n(\rho_n+(1-\alpha_n+\alpha_n\mu_{nt})\gamma_n I_n+(1-\mu_{nt})\rho_{\theta_n})}E(c^i_{mt}-$
$\overline{c}_m)(c^i_{nt}-\overline{c}_n)$

$EC^m(\gamma_m)=\int_0^\mu C^m(\gamma_m)di=\mu_{mt}C^m(\gamma_m)$

$cov(v_{mt}-p_{mt},v_{nt}-p_{nt})=f_mf_nEC^m(\gamma_m)C^n(\gamma_n)=f_mf_n\sigma_{mn}$

Since $f_m=\frac{(1-\mu_{mt})(\rho_m+\gamma_m I_m)(\mu_{mt}\alpha_m I_m\gamma_m+(1-\mu_{mt})\rho_{\theta_m})}{\alpha_m I_m\gamma_m(\rho_m+(1-\alpha_m+\alpha_m\mu_{mt})\gamma_m I_m+(1-\mu_{mt})\rho_{\theta_m})}>0, f_n>0,\ \sigma_{mn}>0$, we have $cov(v_{mt}-p_{mt},v_{nt}-p_{nt})>0$ ■

Proof of Proposition 9.

By proposition 8, $\frac{\partial(cov(v_{mt}-p_{mt},v_{nt}-p_{nt}))}{\partial\mu_{mt}} = \frac{\partial f_m f_n \sigma_{mn}}{\partial\mu_{mt}} = f_n\sigma_{mn}\frac{\partial f_m}{\partial\mu_{mt}}$

We can calculate $\frac{\partial f_m}{\partial\mu_{mt}}$ first.

$$\begin{aligned}
\frac{\partial f_m}{\partial\mu_{mt}} &= \frac{\partial\frac{(\rho_m+\gamma_m I_m)(\mu_{mt}\alpha_m I_m\gamma_m+(1-\mu_{mt})\rho_{\theta_m})}{\alpha_m I_m\gamma_m(\rho_m+(1-\alpha_m+\alpha_m\mu_{mt})\gamma_m I_m+(1-\mu_{mt})\rho_{\theta_m})}}{\partial\mu_{mt}} \\
&= \frac{(\rho_m+\gamma_m I_m)(\alpha_m I_m\gamma_m-\rho_{\theta_m})}{\alpha_m I_m\gamma_m M} \\
&\quad -\frac{(\rho_m+\gamma_m I_m)(\alpha_m I_m\gamma_m-\rho_{\theta_m})(\mu_{mt}\alpha_m I_m\gamma_m+(1-\mu_{mt})\rho_{\theta_m})}{\alpha_m I_m\gamma_m M^2} \\
&= \frac{(\rho_m+\gamma_m I_m)(\alpha_m I_m\gamma_m-\rho_{\theta_m})(\rho_m+(1-\alpha_m)I_m\gamma_m)}{\alpha_m I_m\gamma_m M^2} \\
&> 0
\end{aligned}$$

So by A15, $\frac{\partial(cov(v_{mt}-p_{mt},v_{nt}-p_{nt}))}{\partial\mu_{mt}} = \frac{\partial f_m f_n \sigma_{mn}}{\partial\mu_{mt}} = f_n\sigma_{mn}\frac{\partial f_m}{\partial\mu_{mt}} > 0$ ■

Proof of Proposition 10.

By proposition 8, $\frac{\partial(cov(v_{mt}-p_{mt},v_{nt}-p_{nt}))}{\partial\alpha_m} = \frac{\partial f_m f_n \sigma_{mn}}{\partial\alpha_m} = f_n\sigma_{mn}\frac{\partial f_m}{\partial\alpha_m}$

We calculate $\frac{\partial f_m}{\partial\alpha_m}$ first.

$$\begin{aligned}
\frac{\partial f_m}{\partial\alpha_m} &= \frac{\partial\frac{(1-\mu_{mt})(\rho_m+\gamma_m I_m)(\mu_{mt}\alpha_m I_m\gamma_m+(1-\mu_{mt})\rho_{\theta_m})}{\alpha_m I_m\gamma_m(\rho_m+(1-\alpha_m+\alpha_m\mu_{mt})\gamma_m I_m+(1-\mu_{mt})\rho_{\theta_m})}}{\partial\alpha_m} \\
&= \frac{(1-\mu_{mt})(\rho_m+\gamma_m I_m)\mu_{mt}I_m\gamma_m}{\alpha_m I_m\gamma_m M} \\
&\quad +(1-\mu_{mt})\frac{(\rho_m+\gamma_m I_m)(\mu_{mt}\alpha_m I_m\gamma_m+(1-\mu_{mt})\rho_{\theta_m})(1-\mu_{mt})\alpha_m I_m\gamma_m}{\alpha_m I_m\gamma_m M^2} \\
&\quad -\frac{(1-\mu_{mt})(\rho_m+\gamma_m I_m)(\mu_{mt}\alpha_m I_m\gamma_m+(1-\mu_{mt})\rho_{\theta_m})}{\alpha_m^2 I_m\gamma_m M} \\
&= \frac{\begin{array}{c}(1-\mu_{mt})(\rho_m+\gamma_m I_m)(1-\mu_{mt})[\mu_{mt}(\alpha_m I_m\gamma_m-\rho_{\theta_m})^2+ \\ (1-\mu_{mt})\rho_{\theta_m}(\alpha_m I_m\gamma_m-\rho_{\theta_m})+(1-\mu_{mt})\rho_{\theta_m}(\alpha_m I_m\gamma_m-\rho_m)\end{array}}{\alpha_m^2 I_m\gamma_m M^2} > 0
\end{aligned}$$

By A16, $\frac{\partial(cov(v_{mt}-p_{mt},v_{nt}-p_{nt}))}{\partial\alpha_m} = \frac{\partial f_m f_n \sigma_{mn}}{\partial\alpha_m} = f_n\sigma_{mn}\frac{\partial f_m}{\partial\alpha_m} > 0$

By propostion 8, $\frac{\partial(cov(v_{mt}-p_{mt},v_{nt}-p_{nt}))}{\partial I_m} = \frac{\partial f_m f_n \sigma_{mn}}{\partial I_m} = f_n\sigma_{mn}\frac{\partial f_m}{\partial I_m}$

We calculate $\frac{\partial f_m}{\partial I_m}$ when $\alpha_m = 1$.

$$\begin{aligned}
\frac{\partial f_m}{\partial I_m} &= \frac{\partial\frac{(\rho_m+\gamma_m I_m)(\mu_{mt}\alpha_m I_m\gamma_m+(1-\mu_{mt})\rho_{\theta_m})}{\alpha_m I_m\gamma_m(\rho_m+(1-\alpha_m+\alpha_m\mu_{mt})\gamma_m I_m+(1-\mu_{mt})\rho_{\theta_m})}}{\partial I_m} \\
&= \frac{-(1-\mu_{mt})\rho_m[\rho_m\rho_{\theta_m}+2\mu_{mt}I_m\gamma_m\rho_{\theta_m}+(1-\mu_{mt})\rho_{\theta_m}^2-\mu_{mt}(I_m\gamma_m)^2]}{I_m^2\gamma_m M^2} \\
&< 0
\end{aligned}$$

Then $\frac{\partial(cov(v_{mt}-p_{mt},v_{nt}-p_{nt}))}{\partial I_m} = \frac{\partial f_m f_n \sigma_{mn}}{\partial I_m} = f_n\sigma_{mn}\frac{\partial f_m}{\partial I_m} < 0$ ■

Proof of Proposition 11.

(i)

$$\frac{\partial E(v_{mt}-p_{mt})}{\partial \alpha_m} = -\frac{\begin{array}{c}(t+1)\delta\alpha_m I_m\gamma_m\overline{x}_m+(\rho_m+\gamma_m I_m)(\mu_{mt}\alpha_m I_m\gamma_m \\ +(1-\mu_{mt})\rho_{\theta_m})\overline{c}_m\end{array}}{(M\alpha_m I_m\gamma_m)^2} \tag{A17}$$

$$+\frac{\begin{array}{c}(\rho_m+(1-\alpha_m+\alpha_m\mu_{mt})\gamma_m I_m+(1-\mu_{mt})\rho_{\theta_m}-(1-\mu_{mt})\alpha_m I_m\gamma_m)I_m\gamma_m \\ (t+1)\delta I_m\gamma_m\overline{x}_m+\mu_{mt}I_m\gamma_m(\rho_m+\gamma_m I_m)C^m(\gamma_m)\end{array}}{M\alpha_m I_m\gamma_m}$$

$$= \frac{\begin{array}{c}(t+1)\delta\alpha_m^2(I_m\gamma_m)^3(1-\mu_{mt})\overline{x}_m+(\mu_{mt}(\alpha_m I_m\gamma_m-\rho_{\theta_m})^2 \\ +2\alpha_m I_m\gamma_m-\rho_{\theta_m}(\rho_m+\gamma_m I_m+\rho_{\theta_m}))(\rho_m+\gamma_m I_m)(1-\mu_{mt})I_m\gamma_m\overline{c}_m\end{array}}{(M\alpha_m I_m\gamma_m)^2}$$

$$> 0$$

■

(ii)

$$\frac{\partial E(v_{mt}-p_{mt})}{\partial \mu_m} = -\frac{\begin{array}{c}(t+1)\delta\alpha_m I_m\gamma_m\overline{x}_m+(\mu_{mt}\alpha_m I_m\gamma_m+(1-\mu_{mt})\rho_{\theta_m}) \\ (\rho_m+\gamma_m I_m)\overline{c}_m\end{array}}{(M\alpha_m I_m\gamma_m)^2} \tag{A18}$$

$$(\alpha_m I_m\gamma_m-\rho_{\theta_m})\alpha_m I_m\gamma_m+\frac{(\alpha_m I_m\gamma_m-\rho_{\theta_m})(\rho_m+\gamma_m I_m)\overline{c}_m}{M\alpha_m I_m\gamma_m}$$

$$= \frac{(\alpha_m I_m\gamma_m-\rho_{\theta_m})}{(M\alpha_m I_m\gamma_m)^2}[(\rho_m+\gamma_m I_m)(\rho_m+(1-\alpha_m)\gamma_m I_m)\alpha_m I_m\gamma_m\overline{c}_m -(t+1)\delta^2(\alpha_m I_m\gamma_m)^2\overline{x}_m]$$

$$\overline{c}_m = EC^m(\gamma_m)=\mu_{mt}$$

$$\gamma_m^* = Max\{0,\gamma_m \left| \exp(\frac{-C^m(\gamma_m)^2+2C^m(\gamma_m)(LE(p_{mt}))}{2(\rho_m+\gamma_m(1-\alpha_m)I_m+\rho_{\theta_m})^{-1}\delta^{2-1}})=1\right.\}$$

$$0 < C^m(\gamma_m) \leqslant C_m^*$$

Then we could get $\frac{\partial E(v_{mt}-p_{mt})}{\partial \mu_m} < 0$ ■

Proof of Proposition 12.

$$\frac{\partial E(v_{mt}-p_{mt})}{\partial C^m(\gamma_m)} = \frac{(\mu_{mt}\alpha_m I_m\gamma_m+(1-\mu_{mt})\rho_{\theta_m})(\rho_m+\gamma_m I_m)}{(\rho_m+(1-\alpha_m+\alpha_m\mu_{mt})\gamma_m I_m+(1-\mu_{mt})\rho_{\theta_m})\alpha_m I_m\gamma_m} > 0 \tag{A19}$$

$$\frac{\partial E(v_{mt}-p_{mt})}{\partial \gamma_m} = -(\frac{(t+1)\delta\alpha_m I_m\gamma_m\overline{x}_m+(\rho_m+\gamma_m I_m)(\mu_{mt}\alpha_m I_m\gamma_m+(1-\mu_{mt})\rho_{\theta_m})C^m(\gamma_m)}{(M\alpha_m I_m\gamma_m)^2})$$

$$+\frac{[(1-\alpha_m+\alpha_m\mu_{mt})\gamma_m I_m+(\rho_m+(1-\alpha_m+\alpha_m\mu_{mt})\gamma_m I_m+(1-\mu_{mt})\rho_{\theta_m})]\alpha_m I_m}{M\alpha_m I_m\gamma_m}$$

$$\frac{(t+1)\delta\alpha_m I_m\overline{x}_m+\mu_{mt}\alpha_m I_m(\rho_m+\gamma_m I_m)C^m(\gamma_m)+(\mu_{mt}\alpha_m I_m\gamma_m+(1-\mu_{mt})\rho_{\theta_m})I_m C^m(\gamma_m)}{M\alpha_m I_m\gamma_m}$$

$$\begin{aligned} &= \frac{(1-\mu_{mt})\alpha_m I_m C^m(\gamma_m)[\mu_{mt}\rho_m(\alpha_m I_m\gamma_m-\rho_{\theta_m})^2-\rho_{\theta_m}(1-\alpha_m)(\rho_m+\gamma_m I_m)^2+ \rho_{\theta_m}\rho_m(\alpha_m\rho_m+\rho_{\theta_m})]}{(M\alpha_m I_m\gamma_m)^2} \\ &> 0 \end{aligned}$$

■

REFERENCE

[1] Bailey, W., K. Chan and P. Chung, 2000, Depository Receipts, Country Funds, and the Peso Crash: The Intraday Evidence, Journal of Finance 55, 2693-2717.

[2] Bailey, W., G. Andrew Karolyi, and Carolina Salvac, 213, The Economic Consequences of Increased Disclosure:Evidence from International Cross-listings, Journal of Financial Economics 81,175-213

[3] Bailey, W., Kee-Hong Bae and Connie X. Mao, 2006, Stock Market Liberalization and the Information Environment, Journal of International Money and Finance 25, 404-428.

[4] Barberis, N., A. Shleifer and J. Wurgler, 2005. Comovement, Journal of Financial Economics, 75, 283-317.

[5] Barlevy, G., Veronesi, P., 2000. Information acquisition in financial markets. Review of Economic Studies 67, 79–90.

[6] Bekaert G., C.R. Harvey and A. Ng., 2005, Market Integration and Contagion, Journal of Business, 39-69.

[7] Bekaert, G., R. Hodrick and X. Zhang, 2005, International Stock Return Comovements, Working Paper.

[8] Bharttacharya and Daouk, 2002, The World Price of Insider Trading, Journal of Finance 57, 75-108.

[9] Brennan, M., and H. Cao, 1997, International Portforlio Investment Flows, Journal of Finance 52, 1851-1880.

[10] Brown, D.P., Jennings, R.H., 1989, On technical analysis. Review of Financial Studies 2, 527–551.

[11] Brunnermeier, Markus K., 2000, Asset Pricing under Asymmetric Information: Bubbles, Crashes, Technical Analysis, and Herding, Oxford University Press, New York.

[12] Botosan, C. 1997. Disclosure level and the cost of equity capital. The Accounting Review 72, 323-349.

[13] Cao, H. H., 1999, The Effect of Derivative Assets on Information Acquisition and Price Behaviour in a Rational Expectations Equilibrium, The Review of Financial Studies 12, 131-161

[14] Diamond, D. and R. Verrecchia. 1981, Information Aggregation in a Noisy Rational Expections Equilibrium, Journal of Financial Economics 9, 221-235.

[15] Diamond, D. and R. Verrecchia. 1991, Disclosure, liquidity, and the cost of capital. Journal of Finance 46, 1325-1359.

[16] Durnev, Art; Randall Morck, Bernard Yeung, and Paul Zarowin, 2003, Does Greater Firm-Specific Return Variation Mean More or Less Informed Stock Pricing? Journal of Accounting Research, 41(5), 797-836.

[17] Easley, David, Soeren Hvidkjaer, and Maureen O'hara,, 2002, Is Information risk a determinant of asset returns? Journal of Finance 57, 2185-2221.

[18] Easley, David, Soeren Hvidkjaer, and Maureen O'hara, 2004, Factoring Information Into Returns, working paper.

[19] Easley, David, Nicholas M. Kiefer, and Maureen O'hara, 1996, Cream-skimming or profit-sharing? The curious role of purchased order flow, Journal of Finance 51, 811-833.

[20] Easley, David, NicholasM. Kiefer, andMaureen O'hara, 1997a, The information content of the trading process, Journal of Empirical Finance 4, 159-186.

[21] Easley, David, Nicholas M. Kiefer, and Maureen O'hara, 1997b, One day in the life of a very common stock, Review of Financial Studies 10, 805-835.

[22] Easley, David, Nicholas M. Kiefer, Maureen O'hara, and Joseph B. Paperman, 1996, Liquidity, information, and infrequently traded stocks, Journal of Finance 51, 1405-1436.

[23] Easley, David and Maureen O'hara, 1992, Time and the process of security price adjustment, Journal of Finance 47, 577-605.

[24] Easley, David and Maureen O'hara, 2004, Information and the cost of capital, Journal of Finance 59,1553-1583.

[25] Epstein, L., and Tumbull, S. 1980. Capital asset prices and the temporal resolution of uncertainty. Journal of Finance 35, no. 3:627-43.

[26] Fama, Eugene F., and Kenneth R. French, 1992, The Cross-Section of Expected Stock Returns, Journal of Finance 47, 427-465.

[27] Fama, Eugene F., and Kenneth R. French, 1993, Common Risk Factors in the Returns on Stocks and Bonds, Journal of Financial Economics 33, 3-56.

[28] Fama, Eugene F., and Kenneth R. French, 1995, Size and Book-to-Market Factors in Earnings and Returns, Journal of Finance 50, 131-155.

[29] Fama, Eugene F., and Kenneth R. French, 1996, Multifactor Explanations of Asset Pricing Anomalies, Journal of Finance 51, 55-84.

[30] Fama, Eugene F., and Kenneth R. French, 1998, Value Versus Growth: The International Evidence, Journal of Finance 53, 1975-1999.

[31] Gregory H. Bauer and Clara Vega, 2004, The Monetary Origins of Asymmetric Information in International Equity Markets, Working Paper.

[32] Griffin, J. and A. Karolyi, 1998, Another Look at the Role of the Industrial Structure of Markets for International Diversification Strategies, Journal of Financial Economics 50, 351-373.

[33] Grossman, Sanford J., and Joseph Stiglitz, 1980, On the impossibility of informationally efficient markets, American Economic Review 70, 393-408.

[34] Grundy, B.D., McNichols, M., 1989, Trade and the revelation of information through prices and direct disclosure.Review of Financial Studies 2, 495–526.

[35] Hameed, Allaudeen; Morck, Randall and Bernard Yeung, 2005, Information Markets, Analysts, and Comovement in Stock Returns, NYU Working paper.

[36] Heston, S. and K. G. Rouwenhorst, 1994, Does industrial structure explain the benefits of international diversification? Journal of Financial Economics 46, 111-157.

[37] Holden, Craig W. , and. Avandihar Subrahmanyam, 2002, News events, information acquisition, and serial correlation, Journal of Business 75, 1-32.

[38] Kandel, Eugene, and Neil D. Pearson, 1995, Differential Interpretation of Public Signals and Trade in Speculative Markets, Journal of Political Economy 103, 831-872.

[39] Karolyi, G. Andrew, 1998, Why Do Companies List Their Shares Abroad? A Survey of the Evidence and its Managerial Implications, V7, No. 1, Salomon Brothers Monograph Series, New York University.

[40] Karolyi, A., 2003, Does International Finance Contagion Really Exist, International Finance 6, 179-199.

[41] Kim, O. and R. Verrecchia. 1994. Market liquidity and volume around earnings announcements. Journal of Accounting and Economics 17, 41-67.

[42] Lee, Charles M.C., and Mark J. Ready, 1991, Inferring trade direction from intraday data, Journal of Finance 46, 733-746.

[43] Longin, F. and B. Solnik, 1995, Is the correlation in international equity returns constant: 1960-1990? Journal of International Money and Finance 14, 3-26.

[44] Longin, F., and B. Solnik, 2001, Extreme Correlation of International Equity Markets, Journal of Finance, 56, 649-676.

[45] McNichols, M. and B. Trueman. 1994. Public disclosure, private information collection, and short term trading. Journal of Accounting and Economics 17, 69-94.

[46] Pindyck, Robert and Julio Rotemberg (1993) \The Comovement of Stock Prices." Quarterly Journal of Economics 108, 1073-1104.

[47] Timmermann, Allan and Massimo Guidolin, 2006, An econometric model of nonlinear dynamics in the joint distribution of stock and bond returns, Journal of Applied Econometrics 21, 1-22.

[48] Zhang, G. 2001. Private information production, public disclosure, and the cost of capital: theory and implications. Contemporary Accounting Research 18, 2, 363-384.

[49] Veldkamp, Laura L., 2006, Information Markets and the Comovement of Asset Prices, Review of Economic Studies 73, 823-845.

[50] Verrecchia, Robert E., 2001, Essays on disclosure, Journal of Accounting and Economics 32, 97–180.

Chapter 5
Conclusion

My current research focuses on various issues related to asset pricing. Asset pricing is an important topic for academics, investment professionals, and policy makers. The asset pricing theory tries to understand why prices or returns are what they are. We can have different applications by using asset pricing theory. If the investment world does not obey a model's predictions, we can decide that the model needs improvement. We need to find better model to predict equity returns. However, we can also decide that the investment world is wrong, that some assets are "mispriced" and present trading opportunities for the shrewd investor. This latter use of asset pricing theory accounts for much of its popularity and practical application.

The first essay of my dissertation aims to test an important hypothesis in financial economics: whether equity returns are predictable over various horizons? The conventional wisdom in the literature is that aggregate dividend yields strongly predict excess returns, and the predictability is stronger at longer horizons (Fama and French (1988), Campbell (1991), and Cochrane (1992)). In contrast, Ang and Bekaert (2007) find that dividend yields, together with the short rate, predict excess returns only at short horizons, and do not have any long-horizon predictive power. In this paper, we undertake an analysis of both in-sample and out-of-sample tests of equity return predictability to better understand the empirical evidence on return predictability over different time horizons. We first propose a nonparametric test to examine the predictability of equity returns, which can be interpreted as a signal-to-noise ratio test. Our empirical results show that the short rate, dividend yields and earnings yields have good predictability power for both short and long horizons, which is different from both the conventional wisdom and Ang and Bekaert (2007). Also, using our nonparametric test, a comprehensive in-sample and out-of-sample analysis documents that the predictor variables (dividend yields, earnings yields, dividend payout ratio, short rate, inflation, book-to-market ratio, investment to capital ratio, corporate issuing activity, and consumption, wealth, and income ratio) have predictability power on equity returns but this cannot be well captured by linear prediction models. In addition, we use the nonparametric test to compare the conventional long-horizon prediction regression models on predictor variables with the historical mean model, where there has exists a debate about which model has better forecasting power for equity returns (Campbell and Thompson (2007) and Goyal and Welch (2007)). We find that the prevailing prediction model has a better forecasting power than the historical mean model because the former has a lower neglected signal-to-noise ratio. Finally, our nonparametric predictive models have lower RMSE than the historical mean model at both short-horizon and long-horizon. Using our nonparametric methods, both combined and individual forecast outperform the historical average.

The second essay of my dissertation is to investigate the trading behaviors of three similar trading vehicles: American depositary receipts (ADR), exchange-traded funds (ETF), and closed-end funds (CEF), which specialize in holding a portfolio of foreign equities of one country or a group of countries in a region on US stock exchanges. I focus on how the trading activities differ, in real time, among ADR, ETF, and CEF. First, this essay examines whether ADR, ETF, and CEF trade at different transaction prices across countries. It helps me to understand whether one type of security have an advantage of trading over the other. Second, I use the VAR model to estimate the correlations of return, volume, liquidity, and volatility among the three securities. It shows the relative relation of trading among the three securities. Third, I examine the short-horizon dynamic relation between the order imbalance and both past and subsequent returns by type of securities using high-frequency intraday data. I find that ADRs trade at transaction prices that are on average worse than ETFs and CEFs. The trading of ADRs, ETFs, and CEFs follows positive feedback strategies. The buy and sell trades of the three securities are driven by the net order imbalances and past returns of three securities themselves. The correlated trading behaviors of the three securities can be explained by momentum traders with a common information set.

The third essay of my dissertation introduces endogenous costly information acquisition that generates comovement of asset returns in a rational expectations framework. The private information signals observed by many investors contain information not only about the value of the asset itself, but also the value of many other assets. This common source of information causes excessive covariance in their returns. If informed investors acquire more private information, or more investors are informed, the comovement of asset returns will increase. On the other hand, if informed investors aggressively obtain abundant private information, the comovement will decrease. We also find that both greater precision in private information and higher cost of information will increase a company's cost of capital.

For my future research, I plan to extend my current research in two directions. One research line is still along the predictability of equity returns. I will investigate the predictability of disaggregated returns, such as the returns on value-stocks and the returns on growth stocks over different time horizons. Value-stocks could respond more strongly to dividends, while growth stocks could respond more strongly to book-market factors. The other direction is to investigate whether bond returns are predictable. Though the expectations model works well in the long run, a steeply upward sloping yield curve means that expected returns on long-term bonds are higher than on short term bonds for the next year. The expectations hypothesis seems to do poorly at short (one-year) horizons, but reasonably well at longer horizons. If the expectations hypothesis does not work at one-year horizons, then there is money to be made. One must be able to foresee years in which short-term bonds will return more than long-term bonds and vice versa, at least to some extent. I am also interested in revisiting the hypothesis and puzzles in international finance and empirical macroeconomics.